

**The Effect of Unobserved Plan Attributes on the Health Plan
Choices of Twin Cities Medicare Beneficiaries**

**A THESIS SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL OF THE
UNIVERSITY OF MINNESOTA
BY**

Katherine Marie Harris

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**IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY**

June 1996



THE END OF THE WORLD

UNIVERSITY OF MINNESOTA

This is to certify that I have examined this copy of a doctoral
thesis by

Katherine Marie Harris

and have found that it is complete and satisfactory in all
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GRADUATE SCHOOL

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Abstract

The design and evaluation of policy interventions intended to influence the nature of the Medicare health plan market requires an understanding of the elderly's health plan choice process. To date, such an understanding has been hampered by researchers' inability to measure and include all of the health plan attributes that matter to elderly decision makers in empirical models of health plan choice. Quality of care from the perspective of consumers is an important example. This study addresses this problem by controlling for the effect of cost sharing and unobserved quality of care on plan choice. This study employs a new approach to specification and estimation of choice model parameters that treats these unobserved attributes as latent variables. The approach draws heavily from models of brand choice behavior as well as from recent advances in econometric methods for estimating discrete choice models.

Results suggest that Twin Cities Medicare beneficiaries perceived the quality of care in the fee-for-service supplemental plans to be greater than that in the health maintenance organizations. Also, supplemental plans in the analysis were perceived as having greater quality of care than the basic Medicare entitlement. Finally, Twin Cities elderly perceived the managed care and the fee-for-service sector as offering comparable levels of convenience.

Dedicated to my three grandmothers:

Gladys Hall, Dorothy Harris, and Edna Hall.

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Chapter I: Introduction

Medicare is the federal health insurance program for elderly Social Security recipients. Medicare requires substantial cost sharing and leaves many services uncovered. The majority of elderly enroll in some form of private health plan to supplement the gaps in Medicare. With the goal of improving Medicare outcomes, policy makers have intervened numerous times over the past several decades to influence beneficiaries' supplemental plan choices. These policies include the establishment of HMO risk contracts, the expansion of the Medicare entitlement to eliminate the demand for many types of supplemental plans, the dissemination of consumer information, and regulatory standards for fee-for-service supplements. Recent policy proposals seek to achieve improved Medicare outcomes by creating a payment system which permits beneficiaries to choose among competing health plans on the basis of cost and quality (Dowd et al., 1996). Implicit in these proposals is a public sector role in the collection and dissemination of meaningful information about cost and quality.

An understanding of the elderly's health plan choice process facilitates the design of such interventions and evaluations of their effectiveness. To date, this understanding has been hampered by researchers' inability to measure and include all of the plan attributes that matter to elderly decision makers in models of health plan choice. In general, attributes which are more subjective in nature are

more difficult to measure. Quality of care from the perspective of consumers is an important example.

This study addresses this problem by developing a method to control for the effect of theoretically relevant but unobserved attributes in a health plan choice model. This new method allows researchers to treat decision makers' perceptions of the unobserved plan attributes as model parameters to estimate. The idea is that given a measure of attribute importance, the researcher can learn about perceptions of that attribute by observing choice. The more importance that a decision maker places on a particular attribute, the more the decision maker will prefer the alternative that is perceived as offering more of that attribute. Ultimately this approach may prove useful as an alternative to consumer satisfaction as a perceived quality of care measure and in the development and evaluation of efforts to inform consumers about health plan alternatives.

An important difference between this study and earlier research on health plan choice is the use of information about attribute importance as a measure of preference. Other studies use demographic characteristics of decision makers as proxies for individual variation in preferences. The problem with this approach is that it is too general to answer research questions about the impact of public policies aimed at influencing the characteristics of health plans. This generality stems from a lack of theory about the relationship between demographic characteristics and preferences for

specific plan attributes. The use of attribute importance measures avoids this problem by providing information about preferences that is explicitly tied to particular attributes.

There are other ways to learn about the effect on plan choice of attributes that are difficult to measure directly. Although this information is not routinely collected, researchers could ask decision makers about their perceptions of plan attributes for each plan alternative and include the responses as variables in health plan choice models. Alternatively, researchers can use an experimental design where subjects are asked to indicate their preferences among hypothetical health plans that offer varying amounts of the otherwise unmeasured attributes. However, time and financial constraints may make it difficult to design an experiment such that the results generalize to the population of policy interest.

Despite potential appeal, these approaches are unlikely to satisfy those who are skeptical about the validity of subjective survey data and about the ability to generalize from hypothetical choice scenarios to actual choice behavior (Manski, 1994; Baily, 1980; Sen, 1978). Unfortunately, non-experimental methods for estimating the utility contribution of unobserved attributes that do not use subjective data rely on costly panel data. Thus, the ability to identify and estimate perceptual parameters with cross-sectional choice data represents an important methodological contribution.

The method developed in this study is used to answer two questions previously unaddressed in the health plan choice literature:

- Q1: How do the elderly's perceptions of unobserved health plan attributes vary across health plans?
- Q2: How does controlling for unobserved attributes affect inferences about observed attributes?

Attributes related to quality of care and convenience are treated as unobserved and attributes related to finances, coverage and organizational characteristics are treated as observed. This study provides estimates of the perceived differences in health plan quality of care and plan convenience using data from a 1988 survey of elderly Medicare beneficiaries living in Minneapolis-St. Paul (Twin Cities), Minnesota. Also provided are estimates of the effect of observable financial attributes of plans and covered services on plan choice, controlling for perceived quality of care and perceived convenience.

The resulting parameter estimates suggest that the Twin Cities elderly perceived the quality of care in health maintenance organizations (HMOs) as being lower than that offered by medigap plans. Results also suggest that simply omitting theoretically relevant but unobserved attributes from the choice model specification may lead to misleading inferences about the effect of covered benefits on choice.

The results are used to simulate the effect on choice probabilities of an intervention that eliminates perceived differences in quality of care across health plans. The intervention increases enrollment in the HMO sector by as much as 12 percent, with the strongest effect on those who care the most about quality. However, the effect depends heavily on assumptions about the effect of information on perceived quality within the fee-for-service (FFS) plans.

The following provides an overview of the study. Each section provides a summary of the major topics and findings covered by each chapter.

Medicare and Supplemental Health Plans.

The elderly's health plan choices can not be understood in isolation. The type and level of services covered by the Medicare entitlement determine what forms of coverage will be offered and purchased in the supplemental plan market. Chapter II begins with a description of the Medicare entitlement and the health plans that fill gaps in Medicare coverage. Medicare is the federal health insurance program for elderly Social Security recipients. In 1993, Medicare spend a total of \$154.2 billion at an annual average cost of \$4,173 per beneficiary (Prospective Payment Commission, 1995). Despite this level of expenditure, Medicare is not comprehensive. Medicare requires substantial coinsurance and deductibles. In addition, many costly and valued services are uncovered ("Beyond Medicare", 1989). Uncovered services

include preventive care, outpatient prescription drugs, and long-term care associated with chronic illnesses. In addition, Medicare limits reimbursement to care delivered by certified providers and to an amount that Medicare defines as reasonable.

Many elderly fill gaps in Medicare by enrolling in a supplemental health plan. About 89 percent of the elderly are enrolled in some type of supplemental plan (Chulis et al., 1993a). The remaining 11 percent have Medicare as their only source of health insurance. About one third of the elderly receive supplementary plans from their former employer or labor organization as a retiree benefit (Chulis et al., 1993a). The remaining two thirds of the elderly must purchase their plans from the individual market. Individual plans tend to be more costly and less comprehensive than employer-sponsored health plans (Jensen and Morrissey, 1992).

In general, there are two types of supplemental plans: traditional fee-for-service, or 'medigap', plans and health maintenance organizations (HMOs). Medigap plans allow enrollees unlimited choice of provider, require the enrollees to submit claims for reimbursement when they use services, and frequently limit reimbursement to Medicare covered services and Medicare definitions of reasonable charges. In an increasing number of market areas, Medicare beneficiaries may also enroll in HMOs. HMOs virtually eliminate cost sharing, restrict enrollees to an affiliated service delivery organization and eliminate the need to submit claims.

Chapter II also discusses outcomes of the Medicare program and ways in which policy makers have sought to improve outcomes by influencing supplemental health plan choices. Over the past several decades, policy makers have intervened numerous times to influence health plan choices. For example, policy makers have used regulatory authority to set standards for supplementary plans in an attempt to eliminate low value plans from the market. In addition, public concern over the cost of the Medicare program has prompted policy makers to seek ways to control program expenditures without reducing access or quality of care. Based on the potential of managed care to control the growth in total Medicare expenditures, some policy makers have recently proposed the use of market-based incentives to increase enrollment in managed care plans. Understanding the elderly's health plan choice process is an important step in developing policy interventions and in predicting their effects.

A Model of Health Plan Choice.

Chapter III lays out criteria for selecting a model that provides policy makers with useful information about the effect of policy interventions on plan choice. In order to be useful to policy makers, a model should capture the relationship between the variables that policy makers can influence and health plan choice. For this reason, this study uses a multiattribute model of health plan choice.

Chapter III discusses the advantages of multiattribute choice models and analytic problems created by the inability to measure all of the attributes that matter to decision makers. Multiattribute models assume that decision makers view health plans as bundles of attributes, compare these bundles of attributes and choose the health plan with the utility maximizing combination of attributes. Unfortunately, not all the health plan attributes that matter to decision makers are readily observed by researchers.

This study addresses the omitted variable problem by treating health plan attributes that are theoretically relevant but unobserved as latent variables. Parameter estimates are used to represent the value of the unobserved attributes as perceived by the average decision maker. The approach used in this study draws heavily from the marketing research literature on multiattribute brand choice (Green and Wind, 1973) and from recent advances in econometric methods for estimating discrete choice models (Elrod and Keane, 1995; Elrod, 1988). This approach enables researchers to make inferences about decision makers' perceptions of plan attributes by observing (1) the plan choices of elderly decision makers and (2) a measure of the importance that decision makers place on individual plan attributes.

Individual level variation in attribute importance enables the identification of perceptual parameters with cross sectional data. To date, studies that treat unmeasured attributes as latent variables require panel data. However,

panel data on plan choices is costly and time consuming to collect. The feasibility of collecting panel data would become an even more important consideration with the implementation of Medicare reform proposals that restrict plan choice opportunities to annual open enrollment periods (Dowd et al., 1996).

Model Specification and Estimation.

Chapter IV discusses the choice model specification and the procedure used to estimate model parameters. This study uses a heterogeneous logit specification that is extended to include information about attribute importance. Unlike the standard logit model, the extended heterogeneous logit does not suffer from reliance on the restrictive assumption of the independence of irrelevant alternatives. In this study, the attribute importance responses are treated as error-ridden measures of the true underlying preferences. Thus, the probability that an individual chooses a particular plan is dependent on measurement error. This means that the likelihood function contains a complicated integral for which there is no closed form solution. The value of the likelihood function is approximated using Monte Carlo methods and maximized using standard methods. This method is called simulated maximum likelihood estimation.

Data Source.

The data used in this study come from a 1988 survey questionnaire (n=1,274) administered to Medicare (non-

Medicaid eligible) beneficiaries living in the seven county Minneapolis-St. Paul (Twin Cities) metropolitan statistical area. These data were collected as part of a study of the Twin Cities Medicare health plan market funded by the Health Care Financing Administration. Chapter V discusses these data in detail. The survey questionnaire asked respondents to rate fifteen health plan attributes. Attributes related to finances and coverage are observed in the study. Attributes related to quality of care and convenience are unobserved. Overall, sample members placed the greatest importance on attributes related to quality and the least importance on attributes related to convenience.

Sample members were assumed to choose among five types of plans that include three FFS sector plans and two types of HMOs. In this study, the choice set is comprised of (1) basic Medicare entitlement without supplemental coverage, (2) medigap plans without drug coverage, (3) medigap plans with drug coverage, (4) a type of HMO called an independent practice organization (IPA), and (5) network HMOs.

Results.

The first part of Chapter VI discusses the procedure used to select a final model specification. The final model contains two latent attributes representing quality of care and convenience measured from the point of view of a representative decision maker. The final model also accounts for measurement error in the attribute importance responses.

The parameter estimates resulting from the final model specification suggest that the elderly perceive quality of care in HMOs as lower than in the FFS sector. The results also provide evidence of omitted variable bias arising from the exclusion of theoretically relevant but unobserved attributes. Overall, the findings suggest that plan choices are more sensitive to quality of care, covered services and organization characteristics than to premium differences across plans.

Conclusion.

The study concludes with a discussion of the policy and methodological implications of the findings. The fact that the findings were generally consistent with the popular concern about the quality of care in HMOs suggests that the approach developed in this study may prove useful in monitoring the effectiveness of interventions designed to improve choice. Specifically, the perceptual and preference equation parameters could be used to measure a treatment effect resulting from informational interventions.

Nonetheless, a number of methodological issues warrant future investigation. The validity of the perceptual parameter estimates should be assessed by comparing the findings to direct measures of perceived quality. Such consumer evaluations could be included in surveys of plan enrollees now routinely collected as part of efforts to measure and monitor the quality of managed care. Also, the

psychometric properties of the importance measures should be more fully understood. This information could be used to develop a measure of importance that more completely captures the relevant dimensions of health plans and meaningful variation across relevant subgroups of respondents.

Chapter II: The Role of Health Plan Choice in Medicare

The goal of this chapter is three-fold. First, the chapter provides an overview of the Medicare program and the supplemental plans that fill gaps in Medicare coverage. Second, the chapter discusses the outcomes of this 'two-part' financing system in terms of cost, quality and access. Finally, the chapter discusses the relationship between health plan choice and a range of interventions used by policy makers to improve program outcomes.

Overview of the Medicare Program

Established in 1965, Medicare is the federal health insurance program for the elderly. Over 95 percent of persons age 65 and over are covered by Medicare (Prospective Payment Assessment Commission, 1995). The Medicare health insurance program is comprised of two parts:

Part A. The Hospital Insurance Benefits program or 'Part A' covers inpatient hospital care, inpatient drugs, post-acute care at home and in skilled nursing facilities and rehabilitation hospitals. Those age 65 and over who are eligible for Social Security are automatically eligible for Part A services. Payroll taxes paid by current workers finance Part A services.

Part B. The Supplementary Medical Benefits program or 'Part B' covers physician services, outpatient hospital services, outpatient physical and speech therapies, and medical equipment. Receipt of Part B services by Social

Security beneficiaries is voluntary. Monthly premiums paid by beneficiaries and general tax revenues finance Part B services.

Medicare leaves many costly services uncovered. Medicare does not pay for outpatient prescription drugs, most preventive care services, and hospital stays over 150 days (Employee Benefits Research Institute, 1991). Medicare does not cover the cost of nursing home and home care associated with chronic disabilities (Rivlin and Wiener, 1988). In addition, Medicare also requires extensive cost sharing. Beneficiaries are responsible for deductibles associated with each hospital admission, an annual deductible for outpatient services, physician charges in excess of what Medicare defines as reasonable, 20 percent of covered outpatient service charges and a daily charge for care in skilled nursing facilities after the first 20 days (Employee Benefits Research Institute, 1991)

It is important to note that Medicare is not simply a health insurer. Medicare exerts tremendous market power as the nation's largest single purchaser of health care services. In 1993, Medicare expenditures accounted for 28 percent of national hospital expenditures and 20 percent of national physician expenditures (Prospective Payment Assessment Commission, 1995; Vladeck and King, 1995). This "buying power" means that Medicare policy plays a large role in shaping the entire health care delivery system. System-wide effects of Medicare policy include number and

geographical distribution of hospitals; dramatic reductions over the past decade in the use of hospital services and corresponding increases in the use of outpatient services and post-acute care; and the availability of uncompensated care for uninsured and of hospital services for persons living in rural areas (Vladeck and King, 1995; Altman and Ostby, 1991; Coulam and Gaumer, 1990).

Health Plans Supplementing Medicare.

The majority of elderly Americans have a supplemental health plan that helps to fill gaps in Medicare. These plans come from a variety of sources, cover a variety of services, and organize care in a variety of ways.

Plan Types. There are two main types of health plans that supplement Medicare coverage. First, the elderly may purchase traditional fee-for-service (FFS), or "medigap", plans. Medigap plans allow the elderly unrestricted provider choice. However, ownership of a medigap plan does not eliminate out-of-pocket expenditures. Medigap plans often limit reimbursement to those services covered by the Medicare entitlement, to Medicare certified providers, and to Medicare definitions of reasonable charges. Some Medigap plans cover additional services. Three popular services are prescription drugs, some post-acute care in a skilled nursing facility beyond the 150 days covered by the Medicare entitlement, and coverage of physician charges in excess of what Medicare defines as reasonable ("Beyond Medicare", 1989).

Second, in an increasing number of market areas, the elderly may choose to enroll in a health maintenance organization (HMO). (Brown et al., 1993). Unlike FFS plans, HMOs restrict enrollees to a particular service delivery organization. The characteristics of this delivery system determine the degree of provider choice available to the HMO enrollee. Some HMOs are quite liberal, while others are more restrictive. Many HMOs participating in the Medicare risk contracting program (TEFRA) cover benefits beyond the Medicare entitlement, such as prescription drugs and eyeglasses, require little or no cost sharing and charge premiums that are substantially lower than comparable medigap policies (Brown et al., 1993; U. S. General Accounting Office, 1990).¹ In addition, HMO plans reduce paperwork burden because they do not require the elderly to file claims.

HMOs receive a fixed or 'capitated' payment from Medicare in exchange for providing care to enrollees. The incentives for cost control inherent in existing capitated payment systems have raised questions about the quality of care in Medicare HMOs and have focused attention on the development of payment systems that encourage the provision of high-quality, cost-effective care (Luft, 1994).

¹ The availability of these additional services depends, in large part, on the generosity of the capitation, or 'AAPCC', rate that Medicare uses to pay HMOs. This rate is based, in part, on the local cost of Medicare in the FFS sector. In general, HMOs in high cost regions receive more generous payments and thus, offer more services (Feldman et al., 1993).

As of 1994, 8.7 percent of Medicare beneficiaries were enrolled in any form of HMO plan. Between 1991 and 1994, enrollment grew by more than 50 percent (Prospective Payment Assessment Commission, 1995). The enrollment of Medicare beneficiaries in HMOs is higher in markets where HMOs are more established. These markets include California, Minnesota, Nevada and Oregon (Prospective Payment Assessment Commission, 1995; Brown et. al., 1993).

Plan Sponsorship. There are two sources of private supplementary plans: those sponsored by groups comprised predominately of former employers and labor organizations and those purchased in the individual market. Former employers are the most common source of group-sponsored, retiree health plans. Data from the 1984 Survey of Income and Program Participation and the 1987 National Medical Expenditure Survey indicate that between 30 and 35 percent of persons over age 65 have employer-sponsored plans (Chulis et al., 1993a). The 1988 Survey of Twin Cities Medicare Beneficiaries used in this study shows a similar proportion enrolled in employer-sponsored plans. A total of 38 percent of respondents report obtaining their insurance through a group policy with 31 percent of the sample reporting employer sponsorship. In a survey of Medicare supplemental insurance in five states, McCall and Rice (1985) find that 60 to 80 percent of group policies are associated with employers.

Those not in groups often purchase supplemental plans in the individual market. About 37 percent of the elderly

purchase some type of insurance individually (Chulis et al., 1993a). Of the remaining 30 percent, 12 percent have Medicaid coverage of Medicare gaps and 11 percent do not have any form of supplemental coverage (Chulis et al., 1993a).

Researchers have found substantial socio-economic differences between those who have post-retirement health benefits sponsored by former employers and those who do not. Monheit and Shur (1989) analyzed data from the 1987 National Medical Expenditure Survey. They found that 51 percent of white, retired persons have employment related coverage compared to 35 percent of blacks and 26 percent of Hispanics. They also found wide variation in employment related coverage by industry of former employment. Retirees who worked in white collar, manufacturing or public sector jobs have higher probabilities of employment related coverage than do those who worked in low skilled, service sector jobs or those who were self-employed. Using data from the 1987 Survey of Income and Program Participation, Shea and Stewart (1994) show that higher income levels are associated with a greater likelihood of employer related coverage.

Jensen and Morissey (1992) analyzed data from a survey conducted by the Health Insurance Association of America in 1988. They found that more than 50 percent of retirees whose employers offered retiree health benefits were offered some type of HMO option. To date, however, there is little additional data describing HMO enrollment among former employees of firms which offer retiree health benefits and

little descriptive information about the type and cost of covered services provided by retiree HMO options.

Plan Characteristics. Unfortunately, there is not a single source of representative data that fully characterizes the differences between group and non-group plans. Taken together, however, the findings from a number of studies of retirees, current employees and employee benefits managers depict significant differences between FFS plans sold to individuals and those sponsored by employers. In general, employer-sponsored plans offer more generous coverage at lower premiums compared to individual plans.

Three factors explain the relative generosity of employer-sponsored plans. First, the reduced risk of adverse selection associated with group purchases reduces premiums. Second, lower marketing costs associated with groups also reduces premiums. Finally, unlike individual purchasers, employee benefits managers have the market power to demand that insurers provide information about plan performance and have the training and experience to interpret the information in a meaningful way.

Employer-Sponsored Plans. There are a number of differences between employer-sponsored plans and individual. First, employer-sponsored plans tend to offer less 'first-dollar' and more 'last-dollar' coverage than do medigap plans.² Rice and McCall (1985) found that over 97 percent of

² Post-retirement health benefits are structured in one of three ways: (1) coordination of benefits, (2) carve-out, and (3) exclusion. Which of these three systems a firm uses determines what copays and deductibles the Medicare beneficiary will face with the coordination of

supplemental policies sold in six states covered the Medicare hospital deductible, over 80 percent covered the 61-90 day and 91-150 day Medicare hospital coinsurance and over 90 percent covered the outpatient physician coinsurance. These findings are consistent with findings from Cafferata's (1984b) analysis of data from the 1977 National Health Care Expenditure Study.

A 1987 survey of employers by Foster Higgins (1987), an employee benefits consulting firm, reports that 83 percent of firms offer retirees the same deductibles and co-payments as they offer to active employees. At the same time, most employer plans require enrollees to pay coinsurance and deductibles. Foster Higgins (1987) reports 92 percent of employer plans have deductibles of \$100 or more and 60 to 65 percent of employer plans have cost sharing of 10 percent or more for inpatient and outpatient services.

Similarly, Jensen and Morrissey (1992) analyzed data from two nationally representative surveys conducted by the Bureau of Labor Statistics in order to construct a picture of the post-retirement health benefits expected by future retirees. The first survey sampled employees from medium-small and medium size firms in 1986. The second sampled employees in state and local governments in 1987. Jensen and Morrissey (1992) report that 80 to 90 percent of employees offered post-retirement health benefits were offered benefits identical to those of active employees. They found over 80

benefits method being the most generous and the exclusion method being the least.

percent of employees in such firms were subject to cost sharing for outpatient physician services. Fifty to 67 percent of retirees were responsible for a physician services deductible of \$75 or more. Also, majority of retirees were responsible for some level of physician services coinsurance.

Individual Market Plans. In contrast to the group market, the individual medigap market has been under constant scrutiny by consumer advocacy groups and state and federal regulatory agencies (U. S. General Accounting Office, 1991; "Beyond Medicare", 1989; Federal Trade Commission, 1988). Issues of concern to advocates and regulators include (1) abusive sales practices, (2) deceptive marketing materials, (3) poorly educated consumers, and (4) low loss ratios, the percentage of premiums returned as benefits (U. S. General Accounting Office, 1991).

Health Plan Choice Barriers.

Health policy researchers commonly attribute market failures discussed above in the individual health plan market to two factors: (1) the elderly's lack of understanding of the Medicare program and about the health and financial risks they face and (2) the general lack of meaningful information about plan and provider quality.

Knowledge of Health Plan Coverage. In choosing a plan to supplement Medicare, it is important to know what Medicare covers and what it does not. It is also important to know what services are covered by supplemental plans.

However, a number of studies show that the elderly have low levels of knowledge both about the nature of the Medicare program and the coverage provided by supplemental plans (Rice, 1987; McCall et al., 1986; Cafferata, 1984a).

Cafferata (1984b) analyzed data from the 1977 National Health Care Expenditure Survey to identify factors associated with knowledge about health insurance coverage for 11 types of services. Data were collected in two stages. In the first stage, a nationally representative sample of 2,832 respondents were asked about health plan premiums and benefits. In the second stage, researchers obtained information about health plans from group sponsors and insurance companies in order to verify responses from the first stage.

Cafferata found wide variation in the rate of correct responses depending on the type of services. Less than 15 percent of respondents correctly reported coverage for mental health care. At the same time, over 80 percent of respondents correctly reported plan coverage of short-term hospital stays. Cafferata found high levels of knowledge about services which are not covered by Medicare for which the elderly may incur large out-of-pocket costs, such as prescription drugs, eyeglasses and dental services. Cafferata separated incorrect responses into false negatives and false positives. She found that false negatives were more common than false positives. This means that respondents were likely to say that their plan did not cover

a service that was in fact covered than they were to report that their plan covered a service that was not in fact covered.

In general, Cafferata found that knowledge about health insurance coverage is related to factors associated with respondents' experience with the health care system. Cafferata used the background characteristics of respondents to predict the number of correct responses. She found that greater knowledge was positively associated with supplemental plan premiums and the level of medical expenditures. Knowledge was negatively associated with age. Knowledge was greater for respondents with Medicaid coverage of Medicare gaps compared to those with Medicare only. Controlling for other factors, Cafferata did not find that health status, education, or income were strongly associated with knowledge.

The findings from a study of elderly consumers' knowledge of Medicare and supplemental health plans by McCall and others (1986) are generally consistent with those from the Cafferata study. McCall and others used a 1982 survey of 1,650 Medicare beneficiaries living in six states. In the first part of the study, respondents were asked six true-false statements related to the Medicare program and supplemental insurance plans. McCall and others found that respondents were most knowledgeable about frequently used services, such as eyeglasses, prescription drugs and physician care. Respondents were least knowledgeable about infrequently used services, such as inpatient hospital care

and long-term care. Knowledge of Medicare was greater among those who used medical care more intensively. The authors also found education and income positively associated with knowledge. Knowledge was greater among whites and those who reported being married.

In the second part of the study, McCall and others compared respondents' perceptions of services covered by supplemental plans with their actual coverage obtained through their insurance companies. Respondents were knowledgeable about plan coverage of Medicare copayments and prescription drugs. Respondents were less knowledgeable about coverage of hospital stays exceeding 150 days. Respondents were least knowledgeable about coverage of care in a skilled nursing facility. College educated and upper income groups had greater levels of knowledge.

McCall and others (1986) found that lower levels of education and income were associated with a lower levels of knowledge about Medicare coverage. In an analysis of data from the Medicare Current Beneficiary Survey, Chulis and others (1993a) found that low income elderly are least likely to have a supplemental plan. However, it is not clear whether this is the result of the lack or affordability of supplemental plans or the lack of knowledge about the supplemental plan market.

System Outcomes.

How well does the Medicare program meet the needs of elderly beneficiaries and of the taxpayers who finance it? Congress enacted Medicare in 1965 to protect the elderly from impoverishment by the high cost of medical care, a danger precipitated by the lack of a private insurers willing to sell policies to elderly consumers (Vladeck and King, 1995; Rowland, 1991). Since its enactment, Medicare is generally credited with making mainstream medical care services accessible to the majority of elderly (Rowland, 1991).

Medicare is a partial financing system, rather than a comprehensive financing and closed delivery system. Thus, the nature of the interactions of individual Medicare beneficiaries with the health plans and providers helps determine the outcomes of the health care system that serves elderly Americans. The following sections discuss system outcomes and related health policy issues in three areas.

Cost. The level and growth of Medicare expenditures is of perennial concern to policy makers under pressure to reduce the size of the federal budget deficit. In 1993, Medicare expenditures totaled \$154.2 billion (Prospective Payment Assessment Commission, 1995). Medicare spending rose from 14.9 percent of national health expenditures in 1980 to 17.4 percent in 1993 (Prospective Payment Assessment Commission, 1995). Part A expenditures grew at a rate of 13.6 percent per year between 1980 and 1985. With the introduction of the Prospective Payment System in 1983, this

rate of growth slowed to 7.8 percent between 1985 and 1992 (National Center for Health Statistics, 1994). At the same time, Part B expenditures grew at a rate of 16.4 percent between 1980 and 1985. This rate of growth slowed to 11.2 percent between 1985 and 1990 (National Center for Health Statistics, 1994).

The faster rate of growth for expenditures on Part B services is attributed to the introduction of the Medicare Prospective Payment System (PPS) in 1983. PPS changed the way that Medicare paid hospitals by putting hospitals at risk when the cost of providing inpatient services exceeded a fixed payment. This policy had the unintended effect of shifting expenditures toward less controlled outpatient settings (Prospective Payment Assessment Commission, 1995).

Despite the growth of Medicare expenditures and the large role of private plans in supplementing Medicare, concern remains about the burden of out-of-pocket expenses for health services borne by low income groups. The fact that low income groups tend to have poor health status as measured by a number of indicators (Hulka and Wheat, 1985) adds to this concern. In 1987, about a quarter of persons age 65 and over had no private plan supplementing Medicare. Medicaid covers gaps in Medicare for about half of these elderly who are poor enough to qualify (Monheit and Schur, 1989). The other half are responsible for covering gaps in Medicare on an out-of-pocket basis.

Consistent with the concerns of consumer advocates and regulators discussed above, ownership of a supplemental plan is no guarantee against high out-of-pocket costs. Most supplemental plans offer comprehensive coverage of hospital expenses up to 150 days (Rice and McCall, 1984; "Beyond Medicare", 1989). At the same time, supplemental plans offer much less comprehensive coverage for non-hospital services. This uneven coverage is reflected in out-of-pocket expenditures on health care (See Table II.1). The Families USA Foundation (1992), an advocacy group representing the low income elderly, reports that the elderly paid an average of \$90 (1991 dollars) per year on hospital expenses and \$408 (1991 dollars) on physician charges.

At the same time, medigap premiums are not trivial. A 1989 Consumer Reports review of medigap plans advises readers to expect to pay about \$300 per year for an average cost plan and up to \$800 for a more comprehensive plan. The review shows that in 1989 the elderly would have had to pay at least \$600 per year to purchase a plan that offered a substantial outpatient drug benefit ("Beyond Medicare", 1989).

Access. In the United States, health insurance is an important, if not the most important, determinant of access to health care services. As discussed above, Medicare combined with the supplemental plans has largely succeeded in providing the elderly with comprehensive health insurance (Prospective Payment Assessment Commission, 1995; Rowland, 1991). A measure of this success is the fact that prior to

the enactment of Medicare in 1965, only 50 percent of the elderly had any form of private insurance (Vladeck and King, 1995). Today, over 95 percent of the elderly have health insurance.

Despite this success, financial barriers to access remain a problem for low income elderly. This is because low income elderly, who are least able to afford supplemental plans and most likely to be sick, bear the greatest burden of out-of-pocket costs. Though not perfect, service use is a commonly used measure of access. The elderly without any form of supplemental plan use substantially fewer outpatient and hospital services (Prospective Payment Assessment Commission, 1995; Vladeck and King, 1995; See Table II.2).

Quality. The development and implementation of Medicare cost-containment efforts coincides with increasing concern about the quality of health care services purchased by Medicare on behalf of beneficiaries and about the way in which consumers perceive quality of care. Lohr (1990) traces this concern to a number of specific sources: (1) the prevalence of malpractice litigation, (2) the variation in the use of health services not fully explained by measures of need and community resources, (3) the increasing presence of for-profit providers, and (4) the potential negative effects of cost-containment efforts.

Perhaps surprisingly, Medicare cost-containment efforts do not appear to reduce quality of care (at least as measured by outcomes). Between 1983 and 1986 HCFA implemented two

major policy interventions aimed at controlling costs by creating incentives for more efficient use of health care resources. Evaluations of the impact of these interventions on the outcomes of care were conducted to determine whether cost-containment reduced quality. An evaluation of the impact of PPS conducted by the RAND Corporation found that PPS had no effect on mortality following hospitalization for the five diseases studied (Rogers et. al, 1990). At the same time, the finding that PPS increased the likelihood that patients in unstable condition were being released home increased attention to the quality of post-acute and outpatient settings (Coulam and Gaumer, 1991; Rogers et al., 1990).

More controversial are the effects of Medicare HMOs on quality. An evaluation of the effect of HMO settings on quality conducted by Mathematica Policy Research found few differences in outcome (measured by death, hospital readmissions and post admission complications) between patients enrolled in HMOs and those enrolled in the FFS sector (Brown et al, 1993). However, Mathematica found that HMO patients received fewer discretionary tests and procedures, received fewer precautionary antibiotics prior to surgery and were discharged more quickly (Brown et al, 1993).

Carlisle and others (1992) compared patients with acute myocardial infarction enrolled in three different HMOs with those with FFS sector plans. The authors found no differences in mortality across sectors; greater compliance

with process of care criteria in the three HMOs; and more appropriate physical examinations, histories and cardiac monitoring in the three HMOs compared to the FFS sector. The authors also found more appropriate use of diagnostic testing in the FFS sector.

Riley and others (1994) studied differences in stage of cancer at diagnosis between enrollees in FFS Medicare and HMOs. Stage at detection is an important process measure of quality, because early detection is a strong predictor of survival. The authors found that HMO enrollees were diagnosed with stomach cancer later than FFS enrollees. HMO enrollees were diagnosed earlier with breast, cervix, colon and skin cancers. The authors found no difference in the stage at detection for prostate, rectum, buccal cavity, pharynx, bladder, uterus, kidney and ovarian cancers.

Greenfield and others (1995) compared outcomes of care across prepaid and FFS sectors for patients with hypertension and non-insulin dependent diabetes. Outcome measured included physiological status, functional status and mortality over the seven years of the study. The authors found no differences in outcomes across sectors, though the prepaid sector used more general practitioners.

Two studies that compared health outcomes of HMO enrollees to FFS enrollees in the Twin Cities in the 1980s also failed to find harmful effects of HMOs. Wisner (1992), using the same data used in this study, examines differences in physical function and self-perceived health status

controlling for self-selection into health plans. The author finds no differences in predicted function and that HMO enrollees report higher health status. Lurie and others (1994) compared health and functional status measures for elderly Medicaid recipients who were randomly assigned to capitated plans and to traditional FFS. The authors found no differences across sectors for a number of outcomes including death.

Despite evidence that HMO quality is 'no worse' than in the FFS sector, Luft (1994) warns against assuming that all HMOs are similar. In an earlier paper, Luft (1988) notes that most of what we know about quality of care in HMOs comes from studies of mature HMOs operating in markets where cost containment was not as important as it is today. Luft (1994) points out that much of the research on HMO quality does not permit distinctions between different types of HMOs. The study by Carlisle and others (1994) is an exception.

Over the past decade, both public and private sectors have invested considerable effort in developing measures of quality in terms of the process and outcomes of care, systems for monitoring quality of care, and strategies for improving quality of care. As a consequence of these efforts, the philosophy and mechanisms with which Medicare monitors and assures quality of care have undergone significant changes.

Prior to the implementation of PPS, Medicare operated under the implicit notion that higher expenditures were associated with greater levels of quality (Coulam and Gaumer,

1991). In 1983, Congress gave peer-review organizations (PROs) the responsibility for monitoring the effects of PPS on hospital quality. These non-profit organizations, comprised of health care professionals from a number of fields, had the authority to sanction individual providers and hospitals for problems resulting from specific episodes of care. Providers and policy makers have deemed the PRO system as ineffective because of its reliance on 'adversarial' and 'punitive' approaches combined with constraints on its legal and regulatory authority (Vladeck, 1994; Lohr and Schroeder, 1990). A report on quality assurance for the Medicare program issued by the Institute of Medicine and the National Academy of Sciences stressed the importance of shifting the focus away from monitoring specific episodes toward monitoring of process and outcomes.

Consistent with this recommendation, HCFA introduced the Health Care Quality Improvement Program (HCQIP) in 1993. HCQIP represents an effort to introduce existing PROs to 'modern quality management principles' to monitor patterns of care, rather than specific problematic episodes (Vladeck, 1994). Two important components of HCQIP are the development of a set of quality indicators and fostering of collaborative relationships between PRO and local providers (Vladeck, 1994). An intended outcome of the program is information which consumers can use in choosing providers and health plans (Vladeck, 1994).

Quality from the Perspective of Consumers.

Studies of consumer decision making and the medical care satisfaction literature suggest that consumers care about health plan quality (Marquis, 1985; Pascoe, 1983; Ware et al.; 1983; Ware and Davies, 1983) and that attitudes about plan quality influence a number of health related behaviors, including health plan choice (Clement, 1992; Ware and Davies, 1983; Rossiter, et al.; 1989). 'Health plan quality' refers to the non-financial attributes of health plans, such as convenience, continuity, and quality of care.

The notion that policy makers and providers do not necessarily measure quality in the same way as consumers underlies recent efforts to collect subjective quality measures along with technical quality measures. (Cronin, 1994; Gold and Wooldridge, 1994; Sherbourne et al., 1994). Brook (1991) argues that consumers are not competent to judge technical aspects of medical care of importance to policy makers and providers. By contrast, in a review of the literature on consumer assessments of quality, Davies and Ware (1988) argue not only that consumers can distinguish meaningfully between technical and interpersonal aspects of care but also that consumers are capable of judging the technical aspects of care. Regardless, Davies and Ware (1988) argue that from the point view of understanding health behaviors, such as plan choice, quality of care must be defined as whatever consumers believe it to be.

Consumer Definitions of Quality. Evidence from focus groups provides insight into consumer definitions of quality. The Agency for Health Care Policy and Research sponsored a series of six focus groups chosen for geographic and socio-economic diversity. The goal of the activities was to understand the role of consumer information in health plan and provider choices. The Agency found that

In all the focus groups, the technical quality of care was rarely mentioned; even after probes by the focus group moderators, responses still concentrated on providers' communication rather than technical skills (Agency for Health Policy and Research, 1994).

The National Committee for Quality Assurance also sponsored a series of seven focus groups. The goal of the activities was similar to that of the Agency for Health Care Policy and Research. The Committee found that information about

[C]ost and access were most important to consumers, with technical quality information being of secondary importance. If access to services was more assured, however, consumers might place greater importance on technical assessments (Agency for Health Care Policy and Research, 1994).

Finally, the Institute of Medicine sponsored a series of focus groups with elderly Medicare beneficiaries in 1988 and 1989. The goal of the focus groups was to learn more about consumer definitions of, expectations of, and concerns surrounding quality of care to inform the design of a quality review and assurance program for Medicare. Focus group

members were chosen on the basis of ethnic and geographic diversity as well as health insurance coverage and recent experience with the health care system. The Institute found that

A general theme that surfaced quite frequently during the focus groups is that the perceptions of those who receive medical care define and judge the quality of care in ways that are different from those who provide care. Whereas professionals evaluate quality in terms of complex clinical indicators when describing what they mean by quality of care, patients use 'art-of-care' or interpersonal indicators when describing what they mean by quality of care. They may acknowledge (at least indirectly) a lack of information or capacity for making other types of judgments. ...

[M]ost responses centered on the physician's personality and interpersonal skills. These included the amount of time that doctors spend with a patient, how much interest they show in who the patient is and in his or her well-being, how much information they provide, and whether they are compassionate and understanding. ...

Patients felt that they could not trust a physician who was 'ripping off' the Medicare system through professional preoccupation with financial incentives rather than with the patient. ...

Also, important was going to a hospital that was 'not like a factory.'...The quality of an HMO was judged by how easy or difficult it is to schedule an appointment and the amount of waiting time in a physician's office. Again, very few clinical indicators of quality were mentioned (Walker, 1990).

Taken together, the focus group findings suggest that in defining quality of care interpersonal skills of providers are more important to consumers than technical skills.

Lack of Plan Quality Information. Information about plan quality is not regularly disseminated to Medicare

beneficiaries. Unlike financial and coverage attributes, information about quality may be difficult, if not impossible, to obtain from promotional materials and the fine print of plan contracts. Even more problematic is the lack of measures of plan and provider quality that are meaningful from the perspective of consumers. As of the mid-1990s, efforts to inform consumers about health plan quality have been mainly focused on working-age enrollees in employer sponsored plans (Agency for Health Policy and Research, 1994).

As a substitute for formal information, consumers often turn to informal sources, such as their own experiences and the experiences of friends and family (Marquis, 1985; Glassman and Glassman, 1981). Unfortunately, informal sources of information, while readily available, may not be particularly valid or reliable. Because individuals enroll in only one health plan at a time, they are not likely to know about the plan alternatives in which they are not enrolled. Individuals may not even be well informed about their own plan. Encounters with providers are relatively rare events. Thus, individuals are not likely to know whether their experiences are typical. Further, experiences may vary widely from person to person. For example, beneficiaries with chronic illness may interact with providers and plan administrators on a frequent basis. At the same time, beneficiaries without chronic illness may interact with plans infrequently. The result of such

different experiences may be widely different perceptions of health plan quality depending on chronic health status. The reliance on informal information sources is a problem for Medicare to the extent that it reduces competitive pressure to maintain or improve quality in a cost effective manner.

Influencing Health Plan Choices.

The focus of this study is on developing a model of health plan choice that is useful to policy makers in understanding (1) how the policy interventions discussed above influence health plan choices and (2) how health plan choices might ultimately influence Medicare program outcomes discussed above. Interventions can influence choice directly or indirectly through the delivery system. In addition, not all interventions that influence choice are intentional and not all intentional interventions achieve their intended effects.

In general, policy makers can intervene to influence health plan choices in one of three ways by altering:

- (1) the set of plan alternatives,
- (2) the characteristics of plans, and
- (3) beneficiaries' preferences for particular health plans.

The past decade and a half of major Medicare legislation and legislative proposals can be viewed in terms of these three

impacts on plan choice. A number of these interventions are discussed below.

Medicare HMOs. The Medicare HMO Risk Contracting Program, established under the 1982 Tax Equity and Fiscal Responsibility Act (TEFRA), sought to increase the number of plan alternatives by allowing HMOs to enroll Medicare beneficiaries in exchange for a fixed annual payment (Brown et. al., 1993). In addition to cost savings, an important goal of the program was to assure that Medicare beneficiaries had access to the same range of plan alternatives widely available to the working age population (Dowd et al., 1996).

The Medicare HMO Risk Contracting Program appears to increase Medicare expenditures. This is because the system that HCFA uses to pay HMOs does not fully account for the effect of health status on plan choice. HMOs have the potential to be more cost-efficient than the FFS sector, because HMOs operate under a capitation scheme that creates an incentive for providers to practice in a less resource intensive manner. Policy makers intended to capture savings by paying participating HMOs 95 percent of the annual cost of caring for the average Medicare beneficiary in the FFS sector (Rossiter and Langwell; 1988). However, researchers at Mathematica Policy Research found that healthy beneficiaries are most likely to enroll in HMOs and that less healthy beneficiaries are the most likely to disenroll from HMOs. They estimate that this favorable selection costs Medicare 5.7 percent more than it would have cost to care for these

relatively healthy beneficiaries in the FFS sector (Brown et al., 1993).

Medigap Standards. Minimum standards established by the 1980 Baucus Amendment and Medigap standardization (OBRA 1990) are examples of regulatory interventions that influence the characteristics of health plans. The ultimate goal of these standards is to eliminate low value health plans from the market. Regulatory standards are attractive to policy makers because they do not require new public expenditures. Although the regulation of insurance has traditionally been a state role, the 1980 Baucus Amendment established minimum federal standards for coverage and loss ratios of medigap plans. In part, the 1988 Medicare Catastrophic Coverage Act (MCCA) was intended to remedy the failure of minimum standards to address abuses in the medigap market.

The repeal of the Catastrophic Coverage Act renewed concern about the medigap market (U. S. General Accounting Office, 1991; Jones and Demkovich, 1990). In response to continued criticisms about the complexity of policies and industry abuses, the 1990 Omnibus Budget Reconciliation Act (OBRA) required that medigap plans conform to one of ten prototypes. In effect, standardization limited the number of combinations of benefits available to consumers. Promoted by consumer advocacy groups, such as Consumer's Union, the goal of OBRA 1990 was to enhance competition among insurers by making it easier for consumers to compare plans and premiums (Rice and Thomas, 1992; Jones and Demkovich, 1990). In an

evaluation of the standardization regulations, Rice and Thomas (1992) suggest that regulation may unduly restrict consumer choice. They observe that the benefit packages offered by the most popular medigap plan are not duplicated by any one of the prototypes. In addition, the authors note that the high price of the outpatient prescription drug benefits may indicate insurers susceptibility to adverse selection.

The Medicare Catastrophic Coverage Act. This legislation filled in many of the gaps in Medicare, reducing the need for the elderly to purchase supplemental plans by adding a limit on out-of-pocket spending, eliminating the restriction on the number of hospital days, outpatient prescription drugs, respite care and mammography screening (Rowland, 1991). The Catastrophic Act is an example of an intervention that changes plan attributes. The goal of the Catastrophic Act was to expand access to services and reduce costs to elderly who either could not afford to purchase a high value medigap plan or could not negotiate the complex medigap market (Rowland, 1991). Some have suggested that the Catastrophic Act was repealed because policy makers did not anticipate the unwillingness of middle and upper income elderly to pay surtaxes on the extended benefits (Tolchin, 1989).

Increasing Cost Sharing Requirements. Some policy makers have suggested that the growth in Medicare spending may be reduced by increasing Medicare cost sharing. However,

Chulis and others (1993b) warn policy makers that this strategy is unlikely to be effective in reducing demand for services due to the combination of (1) strong preference among elderly for first dollar supplemental coverage and (2) low income elasticity of demand for first dollar coverage resulting in a high proportion of elderly at every level of income with first dollar coverage (Chulis et al., 1993b). As a result, such a policy may serve only to increase premiums, instead of reducing the demand for services as policy makers intended (Chulis et al., 1993b). Further, Chulis and others (1993b) argue that policy holders will be willing to pay premium increases by foregoing consumption of other goods and services.

Market-Based Reforms. Many Medicare reform proposals, spread across a wide ideological spectrum, seek to achieve improved system outcomes through market-based approaches. The idea is to provide the elderly with the means to choose plans on the basis of cost and quality. In turn, more informed decision makers will force health plans and individual providers to reduce cost and raise quality in order to remain competitive. This increased competition, proponents argue, will ultimately lower Medicare expenditures, improve quality and increase access for low income elderly though lower premiums and cost sharing.

Medicare competitive bidding schemes are an example of a market-based approach (Dowd et al, 1996). This proposal is an example of a type of intervention that alters the

characteristics of health plans by changing relative prices. The idea is that HCFA solicits premium bids from insurers who would like to sell qualified health plans. After reviewing the bids, HCFA would contribute an amount equal to the premium in the low cost plan on behalf of each beneficiary. The fixed contribution is intended to give beneficiaries financial incentives to be careful shoppers. This is because beneficiaries would have to spend their own money to enroll in any plan other than the low cost plan.

Information. The dissemination of information about health plans is an example of an intervention that changes beneficiaries' preferences by influencing their perceptions of health plan characteristics. A government role in the collection and dissemination of information is also implicit in the market-based approaches discussed above. Dowd and others (1996) suggest that the creation of a single open enrollment period would facilitate the collection and dissemination of comparative consumer information through greater oversight of marketing activities by regulatory agencies.

There are a number of examples of this type of informational intervention at the state and federal levels. HCFA funded a number of small programs designed to make beneficiaries aware of HMOs following the enactment of the TEFRA HMO program (Davidson, 1988; Varner and Christy, 1986). HCFA also disseminates literature explaining the nature of the Medicare program called The Medicare Handbook and a guide

for purchasing supplemental plans called Guide to Health Insurance for People with Medicare (U.S. General Accounting Office, 1991). State level informational activities include public service announcements in local media, training of volunteer counselors, seminars and workshops (U.S. General Accounting Office, 1991).

Summary.

Medicare is the federal health insurance program for elderly Social Security recipients. Medicare leaves many costly and valued services uncovered. Most elderly supplement gaps in Medicare by enrolling in a FFS medigap plan or in an HMO. Medicare is not a closed financing and delivery system. For this reason, policy makers have often tried to influence elderly's health plan choices to achieve Medicare program outcomes, in terms of cost, access and quality. It is important to understand the health plan choice process to predict the impact of these policies on outcome goals. Alternative approaches to modeling this process are discussed in the next chapter.

Table II.1: Annual Elderly Family Out-of-Pocket Health Expenditures for Selected Years between 1961 and 1991 (1991 dollars)

Per Family Out-of-Pocket Expenditures					
Year	1961	1972	1984	1989	1991
Total	\$1,589	\$1,854	\$2,698	\$3,249	\$3,305
Hospital	228	175	83	91	90
Physician	316	184	424	392	408
Nursing Home	287	582	972	1,173	1,194
Other	454	390	419	606	640
Private Insurance	304	309	553	619	653
Medicare Premium	na	214	247	368	320
Percent of After-Tax Income					
Year	1961	1972	1984	1989	1991
Total	10.6%	10.6%	16.2%	16.6%	17.1%
Direct out-of-pocket	8.6	7.6	11.4	11.5	12.1
Private insurance	2.0	1.8	3.3	3.2	3.3
Medicare Premium	na	1.2	1.5	1.9	1.7

SOURCE: Families USA Foundation, 1992.

Table II.2: Services Used by Medicare Beneficiaries by Type of Supplemental Plan

Type of Plan	Total	No Use	Physician Only	Inpatient Hospital
Medicare Only	9.1	18.4	7.9	7.5
Medicare + Employer sponsored plan	42.8	39.4	44.8	41.9
Medicare + Individual plan	37.6	33.5	38.8	36.1
Medicare + Medicaid	9.4	7.5	7.1	13.5

SOURCE: Adapted from Prospective Payment Assessment Commission (1995). Medicare and the American Health Care System: Report to Congress. Table 3-16.

Chapter III: Alternative Health Plan Choice Models

Chapter II concluded with a discussion of the ways in which policy makers can intervene to influence health plan choices. This chapter begins with a discussion of the role of conceptual models in understanding the effect of these interventions on plan choice. This chapter lays out a criterion for what constitutes a "good" model when the goal is to predict the impact of public policy interventions on health plan choices. Accordingly, this chapter argues that multiattribute models of plan choice have several advantages over models that treat health plan choice as a function of demographic characteristics.

Nonetheless, researchers confront a number of measurement issues in specifying multiattribute plan choice models with observational data. The most important problem is that a number of theoretically relevant attributes are not readily observable by researchers, with perceived quality being the most notable. This chapter discusses in detail these issues and a range of possible solutions.

Importance of Model Selection

An understanding of the nature of the elderly's health plan choice process is necessary for predicting the effect of public policies intended to influence choice. A conceptual model of health plan choice facilitates such an

understanding. Stokey and Zeckhauser (1978) provide two definitions of conceptual models in the context of policy research:

A descriptive model is just what you would expect: it attempts to describe or explain something, or to predict how some variables will respond to changes in other parts of a system (p. 14).

A model is a simplified representation of some aspect of the real world[.] It is a purposeful reduction of a mass of information to a manageable size or shape. ... [In developing a model,] the analyst must strip away the nonessentials that cloud a problem to expose the structural relationships among the important variables, so the consequence of a particular policy choice may be predicted (p. 8).

These definitions imply that the particular policy question of interest dictates the choice of a conceptual model. In simple terms, a 'good' model is one that accounts for the effect of variables that policy makers can control on the particular outcome of policy interest.

As discussed in Chapter II, policy makers may intervene to influence health plan choice in three ways. First, policy makers may alter the set of health plan alternatives. Second, policy makers may alter the characteristics of the health plans. For example, in 1991 policy makers required that medigap plans conform to one of ten prototypes. Finally, policy makers may provide information that affects decision makers' preferences for or perceptions of health plan characteristics.

According to the definitions above, a research design that seeks to predict the effect of these types of interventions on choices should employ a model that accounts for the impact of policy interventions on the elements of the choice process. Given concern about the gap between actual plan coverage and the elderly's perceptions of plan coverage, it is important that the model be useful in detecting the need for informational interventions and evaluating the effectiveness of consumer information in reducing such misunderstandings.

Alternative Health Plan Choice Models.

Researchers have used several types of conceptual models to explain and predict health plan choices. These models vary in terms of the specificity of the predictions they yield about the effect of policy interventions and the ease of specification with readily available data.

Characteristics of Decision Makers. Much of the policy research related to health plan choices uses a conceptual model that treats choice as a function of the characteristics of decision makers (Dowd et al., 1994; Gertler et al., 1994; Wilcox-Gox and Rubin, 1994; Davidson et al., 1992; Brown et al., 1993; Lichtenstein et al., 1991; McCombs et al., 1990). Characteristics used to predict choice include age, health status, income, educational attainment, gender and ethnicity. In many applications, personal characteristics serve as proxies

for unmeasured elements in the expected utility function, such as risk aversion, the marginal utility of wealth, perceived quality and expected expenditures in each sector (Dowd et al., 1994; Gertler et al., 1994; Davidson et al., 1992; Holmer, 1984). This approach is valuable for addressing a number of policy questions, including those related to the degree of adverse selection across various health plan alternatives and the identification of sub-populations of elderly who have particularly ineffective insurance coverage (Dowd et al., 1993; Brown et al., 1993; McCall et al., 1986).

Despite its wide use, this conceptual model is of limited value in understanding policy interventions (like those described in Chapter II) designed to influence health plan choices by altering characteristics of plans or the set of plan alternatives. A model that relates choice to the characteristics of individuals is too general to capture 'structural relationships' among the relevant policy variables as discussed by Stokey and Zeckhauser.¹ This is because interventions intended to influence choice are not generally designed to affect the characteristics of individuals.

¹ This is not to say that characteristics of decision makers are not important in understanding plan choices. Characteristics of individuals are important for understanding the differential effects of policy interventions or identifying subgroups of elderly in targeting interventions. However, demographic characteristics of individuals are not, in Stokey and Zeckhauser's terms, an essential, structural element in explaining health plan choice.

For example, informational interventions are not intended to influence the age, gender or income of decision makers. Instead, they are intended to change the way that decision makers perceive plan alternatives or to heighten awareness of the importance of certain benefits in reducing financial risk or improving health. A model in which characteristics of individuals determine choice limits inferences to those about the effect of the intervention on the overall probability of enrollment. Information about enrollment probabilities can tell policy makers whether the policy had the intended effect, but provides little insight into why.

Two studies evaluating the impact of HCFA-sponsored informational workshops illustrate this point. Sofaer and others (1990) describe these workshops. Seventy-five workshops were held between October 1986 and May 1987. These workshops discussed Medicare coverage and supplemental plan alternatives, including medigap plans and Medicare HMOs. Researchers collected demographic and health status information from participants. Prior to the workshop, participants were questioned about their knowledge of the Medicare program. Participants were again questioned about their knowledge sometime within a year following the workshop.

Davidson and others (1992) studied the effect of the workshop on plan choices controlling for the characteristics of participants. They found statistically

significant relationships (1) between plan choice and level of knowledge and (2) between plan choice and the interaction between knowledge and health status. This study provides evidence that the workshop intervention influences some aspects of the plan choice process, making it less likely that a participant would remain without a supplemental plan and more likely that a participant would enroll in an HMO. Further, this study showed that the effect of the workshop on this process differed across subgroups of participants.

By contrast, a study using the same data by Gertler and others (1994) provides more insight into the process through which the workshop affected plan choice. Like Davidson and others (1992), the authors use characteristics of individuals to predict choice. However, Gertler and others employ a conceptual model where knowledge gained in the workshop affects the mean and variance of the benefits that decision makers can expect to receive through enrollment in each of the three types of plans. They found that the workshops did not affect the mean level of expected benefits. Rather, they found that the workshop reduced the variance of these expectations. This study provides policy makers with an estimate of the maximum possible impact of information on choices. The authors estimated that the elimination of all uncertainty about benefits would have the same effect

as reducing supplemental premiums by 25 percent. No such prediction is possible with Davidson and others' approach.

Multiattribute Choice Models. Multiattribute decision models address many of the limitations of the model discussed above. Multiattribute models assume that decision makers view choice objects as bundles of attributes and that decision makers choose by comparing these bundles across alternatives and selecting the alternative with the most desirable combination of attributes (Silberberg, 1982; Green and Wind, 1973; Lancaster, 1966). Unlike models that rely on characteristics of decision makers to predict choice, a multiattribute choice model satisfies Stokey and Zeckhauser's (1978) requirement that a conceptual model 'expose structural relationships' among important policy variables. This is because a multiattribute model can link changes in four types of variables that policy makers can use to influence plan choice. These policy variables include:

- (1) Attributes of existing plan alternatives,
- (2) Size and composition of the set of plan alternatives,
- (3) Importance that decision makers place on plan attributes, and
- (4) Perceptions that decision makers have about plan attributes.

Multiattribute decision models are widely applied in economics and in marketing research on brand choice.

Several studies of health plan choice employ multiattribute models (Chakraborty et al., 1994; Feldman et al, 1989; Noord et al., 1989; LaTour et al., 1986; Juba et al., 1980; See Table 4.1). A multiattribute plan choice model can also be written in terms of mathematical relationships. A decision maker's overall judgment of the benefit or utility of enrolling in health plan j can be written

$$(III.1a) \quad U_j = f(x_j) \quad j = 1, \dots, J$$

where x_j is a $1 \times K$ vector of plan attributes measured in physical units and $f(\cdot)$ is a function that maps the plan attributes into the decision maker's subjective utility assessment. The decision maker is assumed to choose the health plan with the highest U_j , $j = 1, \dots, J$.

There are many possible forms of $f(\cdot)$. However, the choice of $f(\cdot)$ is governed by practical concerns. Not only should $f(\cdot)$ make sense conceptually, it should also be computationally tractable with the data that is available to the researcher.

Linear Compensatory Decision Rules. An additive compensatory form of the utility function is popular in applied research in marketing, economics and other social science disciplines (Louviere, 1988; Green and Srinivasan, 1978; Green and Wind, 1973). This type of utility function can be written

$$(III.2) \quad U_j = \beta'x_j$$

where β is a $K \times 1$ vector that represents the importance that the decision maker places on each of K attributes, and x_j is the amount of attribute k in plan j . This form of the utility function assumes that the decision maker forms an overall evaluation by summing the utility contribution of individual attributes. This model is compensatory in the sense that low valuations of one attribute can be offset by high valuations of other attributes.

Green and Srinivasan (1978) reviewed the empirical literature on use of linear compensatory decision rules. Their review summarizes empirical evidence suggesting that decision makers use simpler rules. Nonetheless, the authors suggest that the linear compensatory rule is a good approximation of these simpler rules, especially when the researcher is interested in prediction. Green and Srinivasan (1978) suggest that linear compensatory decision rules perform well when

- (1) utility is monotonically increasing or decreasing over increasing levels of attributes;
- (2) attributes are correlated; and
- (3) there is error involved in measuring attributes.

It is reasonable to expect that these three conditions hold in specifying a health plan choice model with observational data.

Expected Utility Theory. A number of researchers have used expected utility models to explain the decision to purchase health insurance and to predict the effect of tax policy on this decision (Banthin, 1992; Marquis and Holmer, 1986; Keeler et al., 1977; Friedman, 1974).

Existing applications of expected utility theory to health plan choice focus on the effect of two plan attributes:

(1) premiums and (2) expected out-of-pocket spending.

Existing applications of expected utility models have yet to capture the influence of non-financial characteristics on plan choice, thereby limiting their ability to inform policy decisions.

Expected utility maximization is an economic theory of decision making under uncertainty (Varian, 1992; Feldstein, 1988). Similar to the case of decision making under certainty, economic theory assumes that decision makers associate higher levels of wealth with higher levels of utility, or happiness. Expected utility models of plan choice assume that the decision to purchase a health insurance plan amounts to choosing a level of wealth (or consumption of nonmedical care goods) that remains after paying premiums and out-of-pocket expenses. It is the decision maker's health status, wealth, and

taste for medical care consumption that determines the level of out-of-pocket spending. However, decision makers are uncertain about their future health status at the time they must choose whether to insure.

As a consequence of this uncertainty, decision makers do not know how much utility they will derive from each plan. Instead, this theory assumes that decision makers calculate an 'expected' utility score for each plan by summing the utility levels associated with all possible health states weighted by the probability that each health state occurs. Decision makers are assumed to choose the plan with the highest expected utility. According to this theory, the demand for health insurance depends on (1) the decision maker's initial level of wealth, (2) plan premiums, (3) cost sharing requirements, (4) the decision maker's health status as it affects out-of-pocket expenditures, and (4) the degree to which the decision maker is risk averse.

Banthin (1992) specifies and tests an expected utility model of the elderly's supplemental insurance choices using data from the 1977 National Medical Expenditure Survey. Banthin's study is noteworthy for two reasons. First, her study is one of the few, if any, to specify and test a structural expected utility model with choice data gathered from elderly decision makers. Second, she specifies two versions of the expected utility

model, each with a different assumption about the relationship between risk aversion and income.

The two versions of the model produce very different estimates of the degree of risk aversion in the population of elderly decision makers. At the same time, the two versions suggest that the elderly decision makers are insensitive to changes in premiums and cost sharing. The finding that the elderly's plan choices are not influenced by changes in prices may result from the omission from the model of non-financial attributes, such as quality of care.

Identifying Relevant Attributes.

An important step in specifying a multiattribute health plan choice model is identifying the plan attributes that are relevant to decision makers. Green and Wind (1973) offer guidelines useful for selecting which attributes belong in a multiattribute health plan choice model. Although Green and Wind's (1973) proposed criteria were used for purpose of selecting one 'Miss Campus Sweetheart' from a number of worthy contestants, the criteria can be easily adapted to the elderly's choice among health plans:

- (1) No two health plans can share identical attributes and still be treated as distinct alternatives. However, plans with identical attributes can be treated as a single alternative.

- (2) No two attributes can have identical values across all plans and still be treated as distinct attributes. At the same time, no combination of plan attribute levels can imply another plan attribute level. However, identical attributes can be combined into a single attribute.
- (3) The set of plan attributes must be sufficient for decision makers to choose the best plan. In other words, all of the attributes that matter to decision makers must be included in the model.

Information about relevant attributes can come from a number of sources (Shocker and Srinivasan, 1979). First, researchers can directly question decision makers using techniques such as surveys or focus group interviews. Second, researchers can use cluster and factor analytic techniques to identify, post hoc, relevant attributes from data about consumer preferences. Third, researchers can draw on theory or prior literature. Finally, researchers working with experimental research designs may include attributes of particular policy interest, where the effect of such attributes on choice behavior is largely unknown. For example, in a study of purchase intention, Latour and others (1986) tested elderly Medicare beneficiaries' reactions to hypothetical policies, some of which included extended long-term care coverage that was largely unavailable in actual policies.

This study employs the third approach. Research on consumer satisfaction with health care services and health plan choices serves as the source of relevant plan

attributes. Pascoe (1983) reviewed a number of studies that relate characteristics of the health care delivery system to consumer satisfaction. His review found satisfaction related to (1) the accessibility, availability, and convenience of services; (2) financial characteristics, such as premiums and out of pocket expenditures; (3) the nature of provider-patient interactions; (4) the technical competence of providers; (5) the interpersonal skills of providers; (6) length of visit; (7) continuity of care; and (8) the clinical outcomes of care. These eight areas overlap with the six dimensions of medical care found by Ware and others (1983) in using factor analysis to develop the Patient Satisfaction Questionnaire. These dimensions include (1) access; (2) availability; (3) finances; (4) continuity; (5) interpersonal manner; and (6) technical quality. The six dimensions listed above correspond to health plan attributes included in models of health plan choice. These studies are summarized in Table III.1.

Barriers to Measuring Plan Attributes.

Even though the set of attributes that appropriately belong in a health plan choice model is well supported by past research, a number of measurement issues must be addressed in specifying the choice model empirically.

The Meaningful Measure Problem. From whose point of view should plan attributes be measured?

Inferences are more reliable when model variables are defined in terms that are closer to decision makers experiences with health plans. However, policy makers and decision makers do not necessarily view health plan attributes in the same way. As a result, researchers must strike a balance between reliability and the model's ability to yield results that are useful to policy makers.²

It is convenient for policy makers to see health plans in terms of the attributes which they can intervene to control (Myers and Shocker, 1981).³ At the same time, elderly decision makers may view the financial attributes in more subjective ways that may or may not be measured in physical units. The process by which the elderly formulate subjective perceptions of physical characteristics is called 'psychophysical' or 'perceptual' judgment (Louviere, 1988). An example helps to illustrate this process. Consistent with Phelps' (1973) model, assume that in choosing a health plan decision makers care about the amount of non-medical care consumption and the well being that they derive from the consumption of medical care. If this is the case, then decision makers may view plan attributes measured in physical units, such

² This is a classic problem in marketing research. For example, firms define attributes of brands in terms of physical units of chemical ingredients while consumers tend to view attributes of shampoo in terms of the outcomes of use, such as the degree of cleanliness or in more subjective terms, such as the prestige associated with the brand (Mittal et al., 1990).

³ Myers and Shoker (1981) refer to producers of consumer goods, not policy makers. In this context, however, the same argument applies readily to policy makers.

as the total number of covered hospital days, in terms of the increment of well being 'produced' through the use of this service.

To be useful to policy makers, the model must predict behavior in terms that are meaningful and policy relevant. For example, policy makers are interested in the out-of-pocket costs required by various health plan alternatives, not how many restaurant meals the elderly will have to forgo in order to enroll in a more comprehensive plan. Fortunately, these different perspectives on the same attribute are not considered a problem as long as the attributes are measured in units that are meaningful to both policy makers and decision makers (Myers and Schoker, 1982). This means that the model can be useful even without a full understanding of the psychophysical judgment process.

Arguably, this is the case for measuring the financial attributes of health plans in dollar terms. Consumer guides and marketing materials aimed at communicating with elderly consumers describe the financial attributes of health plans in the same financial terms that are meaningful to policy makers. Therefore, it is reasonable to propose that the financial attributes of health plans be measured in dollar terms.

The non financial attributes of health plans are more problematic. First, consider quality of care. There is considerable debate as to whether a common scale that is

meaningful to both policy makers and decision makers even exists. Next, consider convenience. Here, the issue not whether a meaningful scale exists, but rather which one. The convenience of health plans is typically measured in terms of travel and waiting time (Feldman et al., 1989; Juba et al., 1980; Latour et al., 1986; Chakraborty et al., 1994; See Table III.1). No doubt time units are meaningful to both policy makers and decision makers. However, the elderly may measure convenience in other ways. The elderly are more likely relative to the general population to suffer functional impairments (National Center for Health Statistics, 1994). Also, most elderly are not in the work force and the opportunity cost of their time may be lower. As a result, the elderly may measure the plan convenience terms of things like flights of stairs or the availability of public transportation.

The Missing Attribute Problem. A second issue related to measurement is whether policy researchers can readily observe relevant plan attributes. To specify a multiattribute plan choice model, researchers must have a way of measuring the attributes of all alternatives in a decision makers' choice set. However, not all plan attributes can be easily observed, even when the attribute can be readily measured in ways meaningful to policy makers and decision makers. Attributes that are specific to the plan and are related to coverage or financial aspects are readily observable. More difficult to observe

are plan attributes that are specific both to the health plan and to the decision maker. These person-plan specific attributes include travel distance, waiting time and expectations of out-of-pocket costs of enrolling in each plan alternative. These attributes are more difficult and costly to measure because they require information gathered from individual decision makers, not just health plans. This type of information is not typically included in data documenting the plan enrollment of Medicare beneficiaries. Thus, it is difficult to specify multiattribute models of the elderly's health plan choices.

One of the biggest problems researchers face in specifying multiattribute choice models with non-experimental data is the difficulty of observing attributes of alternatives not chosen by sample members. It is easier for researchers to observe the attributes of all alternatives when decision makers are choosing among alternatives from a well defined choice set. This has traditionally been the case in modeling choice among employer-sponsored plans. Researchers can obtain attribute values from marketing materials and plan contracts supplied by a benefits managers, rather than having to obtain the information from each respondent individually. Unfortunately, this is not the case in modeling the elderly's choice of health plan, since the

majority of elderly purchase health plans individually
(See Chapter I).

Consequences of Omitting Relevant Attributes.

The lack of appropriate measures or the inability to observe relevant attributes creates the temptation to simply omit the unmeasured attributes from the analysis. Often researchers assume that the utility contribution of unobserved attributes is absorbed in a random disturbance term. Hausman and Wise (1978) use a random error term to represent both unobserved attributes and unobserved heterogeneity in preferences across decision makers. Rewriting the multiattribute utility function in equation (III.1a) from above, w_j represents attributes which matter to decision makers that are not observed and the vector x^* represents the subset of observable attributes.

$$(III.1b) \quad U_j = f(x_j^*) + w_j \quad j = 1, \dots, J$$

There are two problems associated with the omission of any variable representing theoretically relevant attributes from a health plan choice model specification. First, and most important, if the omission leads to correlated or non-random errors across alternatives then the model is misspecified. This type of misspecification may occur if, for example, unobserved quality in one plan is systematically related to unobserved quality in another

plan. Alternatively, misspecification may occur if unobserved plan quality is systematically related to observed premium levels within the same plan. Ignoring such correlations leads to biased and inconsistent parameter estimates in discrete choice models with the potential to produce misleading policy recommendations (Hausman and Wise, 1978).

Second, it is not possible to draw inferences about the effect of attributes missing from the choice model. Specifically, if the analysis does not account for unmeasured attributes, then there is no way to use the model to make inferences about the effect of a policy intervention designed to alter attributes or perceptions of attributes on plan choices.

Solving Measurement Problems.

Researchers can use a number of strategies to control for the otherwise unobserved attributes.

Develop Proxy Measures. These measures can come from a number of sources. One common source is sample information. Under the first strategy, researchers assign the average value of the attribute in the sample as the value of the attribute not chosen. This approach is taken by Banthin (1992), Gertler and others (1994), and Feldman and others (1989). The assumption here is that decision makers perceive the attributes of the alternatives they did not choose to be some composite of alternatives that

other sample members choose. However, an equally compelling story is that if the alternative was not chosen then the decision maker perceived the attributes to be worse than what was perceived by people who did in fact choose that alternative. For this reason, researchers might want to supplement, or at least validate, sample information about chosen attributes with outside information. Alternatively, it may be possible to develop prototype choices from non-sample information, such as marketing materials, media advertisements and consumer information. The assumption here is that consumers use these sources to inform their perceptions of the alternatives they did not choose.

Consumer Evaluations. Another approach might be to use surveys to elicit consumer perceptions of plan attributes for each plan in the decision maker's choice set.⁴ At the current time, however, this approach is largely hypothetical because such data are not routinely collected for plans other than the plan in which the respondent is currently enrolled. One potential barrier to implementation of this strategy is that the researcher must have full knowledge of the decision maker's choice set at the time of survey construction.⁵

⁴ Examples of consumer evaluation questions might include the following. Rate the quality of care in each of the following health plans: Excellent, good, fair, poor. How friendly are the physicians in each of the following health plans: Very friendly, Somewhat friendly, Not friendly. (See Sherbourne et al., 1994).

⁵ It is not necessary for the researcher to know the full choice set at the time attribute importance information is collected. This is an advantage of the approach used in this study.

Moreover, questions remain about the validity of such information. In general, economists believe that the only way to understand decision maker's attitudes towards alternatives is to observe choices (Sen, 1978). Manski (1995) suggests that economists have been unwilling to collect data on perceptions because of a 'traditional skepticism toward subjective data' resulting from lack of incentive on the part of survey respondents to answer such questions truthfully.⁶

Consumer Satisfaction. Consumer satisfaction data are now routinely collected by health researchers and plan managers (Cronin, 1994; Gold and Wooldridge, 1994; Sherbourne et al., 1994). At first glance, consumer satisfaction measures look like good candidates for inclusion in choice model specifications as indicators of otherwise unobserved quality of care. Satisfaction measures have been shown to be related to health plan choice behavior (Ware and Davies, 1983). Moreover, satisfaction measures are inherently subjective. This subjectivity means that they allow quality, as Davies and Ware (1983) suggest, to be whatever consumers want it to be. Finally, several studies have found that dissatisfaction is a strong predictor of disenrollment

⁶ A study by Baily (1980) measuring the value of reductions in the risk of loss of life illustrates this point. Baily (1980) uses evidence from actual behavior to estimate willingness to pay for risk reduction due to "hopelessly confused and unreliable data" resulting from surveys.

from Medicare HMOs (Clement et al., 1992; Rossiter et al., 1988).

However, two problems reduce the appeal of satisfaction as a proxy for unmeasured attributes in the context of health plan choice. First, more of the unmeasured attribute does not necessarily imply more satisfaction. Satisfaction is commonly conceptualized as measuring the perceived amount of the attribute as well as the gap between the expected amount of the attribute and the experienced amount (Anderson and Sullivan, 1993; Yi, 1993; Pascoe, 1983; Day, 1977). If satisfaction is determined, in part, by expectations, then the relationship between the perceived amount of the attribute and satisfaction is indeterminate. For example, two people who have different perceptions about quality of care may report similar levels of satisfaction because they had different expectations.

Second, satisfaction measures do not convey information about decision makers' perceptions of the health plan alternatives that were not chosen. Decision makers' perceptions of the relative quality of plan attributes is assumed to drive enrollment choices. However, satisfaction is not a measure of relative quality. This is because survey respondents can only meaningfully rate their satisfaction in the plan in which they are currently enrolled.

Experimental Settings. Experimental designs are advantageous in that they allow researchers to control the experimental setting. This means that experimental settings allow researchers to explore consumers' preferences for health plans that do not currently exist. Because experimental designs may involve hypothetical plans with hypothetical attributes, such designs are not hindered by measurement barriers. For example, researchers in experimental settings may simply ask subjects which they would rather choose (while holding other attributes, such as premiums or cost sharing, constant): a plan that requires a 30 minute drive or a plan that requires a 10 minute drive. Researchers using real world data have a much more difficult task. They must determine how far subjects actually drive to reach providers in each plan in the choice set.

Moreover, because researchers have complete control over the level of the plan attributes presented to the subjects, experimental studies can also allow researchers to make inferences that are either very difficult or impossible with observational choice data. This is because, in many cases, the health plan market does not provide natural variation in single attributes or covariation among particular attributes of policy interest. For example, observational data do not provide much natural variation in cost sharing requirements. In addition, benefits like drug coverage and extended post-

acute care coverage are rarely combined in the same medigap plan.

The fact that experimental approaches deal with hypothetical, rather than actual, choices is a significant disadvantage from the perspective of people skeptical about subjective survey data. In experiments, the concern raised by Manski (1994) about subjects' incentive to respond truthfully remains. To the extent that hypothetical choice behavior and actual choice behavior differ, policy recommendations based on the results of experimental data will be misleading.

Further, even if the link between hypothetical and actual choice behavior is strong, it may be difficult to generalize from conclusions drawn from experimental settings (Cook and Campbell, 1979). Cost considerations limit the use of experimental designs to relatively small sample sizes. Financially feasible experimental samples may be too small to permit researchers to generalize to national populations or to sub-populations of policy interest.

Treat Unobserved Attributes as Model Parameters.

An alternative strategy to direct measurement is to treat unmeasured attributes as choice model parameters and to estimate their value. This approach has several advantages. First, unlike direct measurement, treating unmeasured attributes as model parameters does not

necessarily require researchers to know all relevant plan attributes prior to data collection. Therefore, researchers can treat unmeasured attributes as latent variables without specifying dimensionality prior to data collection. Second, researchers can make inferences about unmeasured attributes from data that were not necessarily collected for this purpose. This allows researchers and policy makers to make inferences about these attributes without large investments of time and money in the development of appropriate measures and data collection. Most important, this approach can be used in developing and evaluating informational interventions by allowing researchers to compare parameter estimates representing decision makers' perceptions of attributes to actual attribute levels.

Nonetheless, treating perceptions as parameters has several drawbacks. First, the interpretation of parameter estimates as representing perceptions depends on the validity of the underlying choice model. Second, parameter estimates are scaled according to an unknown metric, thereby complicating interpretation of the resulting estimates.⁷ Finally, parameter identification requires a source of variation in preferences. Not all data sets provide this type of variation.

⁷ A choice model that treats perceptions as parameters can not account for a 'don't know' response category common in surveys. This is because this response does not lie along the assumed continuum.

Choice-Based Market Mapping. Until recently, the treatment of unmeasured attributes as latent variables has been limited to experimental settings. This technique has been widely used by marketing research in experimental settings under the broad heading of 'perceptual mapping' (Shocker and Srinivasan, 1979; Green and Wind, 1973; Green and Carmone, 1970). The goal of perceptual mapping is to gain insight into the degree to which consumers perceive the attributes of competing brands as similar or different. It is not necessary to know the dimensionality of the attributes before hand. In general, the collection of perceptual data requires subjects to rank numerous attribute profiles in terms of similarity or preference (Greene and Wind, 1973). The results of these analyses are used by firms to design new products or to plan promotional campaigns.

Using recent advances in econometric methods for estimating discrete choice models, marketing researchers and economists have developed techniques for estimating perceptual parameters from actual choice data (Elrod and Keane, 1995; Elrod, 1988). This alternative to experimental approaches is called choice-based market-mapping, referred to here as "choice-mapping." The model specification employed in this study draws heavily on this methodology. Choice-mapping uses observed choices to estimate a latent factor structure where factors represent attributes of choices that influence utility. This factor

structure is used to generate a "perceptual map" or a "market map." These maps are used to make inferences about consumer preferences and the position of perceptions in multiattribute space (Elrod and Keane, 1995; Elrod, 1988).⁸ This approach is appealing to economists because it does not rely on hypothetical choices or subjective survey questions.

It is important to point out that the choice-mapping approach relies on the strong assumption of homogeneous perceptions. This assumption implies that all decision makers share the same perceptions of the unobserved attribute regardless of their experience with the health plan. Thus, choice-mapping can not be used to model differences in perceptions between current and potential enrollees or between frequent and infrequent users. Further, the assumption means that choice-mapping does not provide any insight into the uncertainty surrounding decision makers' perceptions or into the degree of consensus among decision makers about the perceived amount of the unobserved attribute.⁹

The assumption of homogeneous perceptions is more reasonable in markets where consumers are regularly provided with comparative information about health plan attributes. The assumption is also more reasonable in

⁸ The resulting parameters are interpreted as representing perceptions under the assumptions that preference weights are constant across alternatives.

⁹ Note that the standard errors surrounding perception parameter estimates are indicators of the researchers' uncertainty about the value of the estimate.

contexts where the perceptual parameter represents an overall impression, rather than an evaluation of a technical detail. For example, consumers may have a general idea of the relative amount of quality of care provided by alternative health plans. At the same time, the same consumers may have no way to judge the degree to which the providers in alternative health plans comply with practice guidelines.

An example helps to convey the substantive interpretation of the results of a choice-mapping analysis. Figure III.1 shows a sample choice map in the case of two dimensions. The location of this plan on the graph indicates the placement of the plan in perceptual 'space.' The position of the plans is meaningful only relative to a reference category represented at the origin, in this case, basic Medicare. The distance between plans is calibrated according to a standardized ratio scale, implying that relative distances, rather than absolute differences, are meaningful.

Figure III.1 suggests that decision makers view plan A, plan B and plan D as having shorter waiting times than basic Medicare. Plan C is perceived as having longer waiting times than basic Medicare. The perceptual map also suggests that plan A and Plan B are viewed as providing higher quality of care than basic Medicare, while plan C and plan D are viewed as having lower quality of care. Finally, the relatively close proximity of plan

A and plan B suggests that these two plans are the closest substitutes along these dimensions, holding other attributes constant. Separate analyses may be performed for different subgroups and the maps may be compared. For example, the perceptual map for decision makers with chronic illness may appear very different compared to a perceptual map corresponding to healthy decision makers.

The choice-mapping methodology combines traditional discrete choice models used by applied economists and policy researchers with perceptual mapping techniques used by marketing researchers and consumer psychologists. The choice-map specification can be derived either from a multidimensional scaling algorithm or from a random utility model (Elrod, 1988). Unlike random utility models used in the applied economics literature, the attributes of choice alternatives do not necessarily have to be observable or even known by the researcher a priori (Elrod and Keane, 1995; Elrod, 1988).

As mentioned above, an important drawback of the choice-mapping methodology from the perspective of policy research is that it requires panel data, or repeated observations on the same unit. Existing applications of the choice-mapping methodology have used supermarket scanner data from consumers who have agreed to have their purchases monitored. However, panel data on health plan choices are more costly and time consuming to collect. The problem is that plan choice opportunities occur less

frequently than supermarket purchases. The availability of sufficient panel data will be come an even bigger hurdle with the enactment of proposals to restrict choice opportunities for Medicare beneficiaries to an annual open enrollment period (Dowd et al., 1996).

Using a Measure of Attribute Importance. This study develops an alternative method for estimating the utility contribution of unobserved attributes that is similar to choice-mapping that does not rely on panel data. This study uses a measure of the importance that decision makers place on particular plan attributes as a source of variation in preferences. The ability to identify and estimate latent variables representing unobserved attributes with cross-sectional data represents an important methodological contribution. Model specification and estimation procedures are presented in Chapter VI.

Economists may see the use of importance measures as a compromise. Reduced reliance on panel data comes at the expense of increased reliance on subjective survey data. At the same time, those who are more comfortable with subjective data and who are more skeptical of utility maximization theory may see less overall value in the ability to infer perceptions from actual choices. Instead, they may prefer to concentrate efforts on the development of survey approaches to measuring perceptions. Nonetheless, any consistency between the estimated values

of the perceptual parameters and survey responses serves to validate both approaches.

Summary.

Multiattribute choice models are useful for understanding the effect on choices of variables that policy makers can intervene to control. These variables include the set of health plan alternatives, the attributes of health plans, and decision makers' perceptions of health plan attributes. In specifying multiattribute models, researchers face the barrier that not all health plan attributes that matter to decision makers can be readily observed. There are a number of potential solutions to this problem. These solutions include developing new measures of the unobserved attribute, turning to experimental methodologies, or treating the unobserved attribute as a model parameter and estimating its value. This study takes the third approach. Unlike earlier studies that require panel data, this study estimates the utility contribution of the unobserved attributes with cross-sectional data.

Figure III.1: Sample Choice-Mapping Results

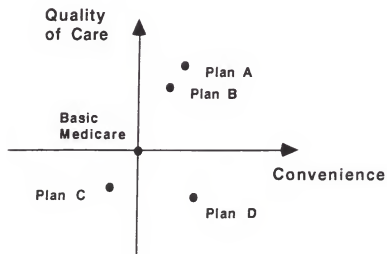


Table III.1: Summary of Studies Using Multiattribute Health Plan Choice Models

	Feldman et al. (1989)	Juba et al. (1980)	LaTour et al. (1986)	Chakraborty et al. (1994)
Overview	Examines employees' choice among employer-sponsored plans.	Examines employees' choice of HMO vs traditional Blue Cross-Blue Shield plan.	Examines purchase intention among Medicare beneficiaries.	Examines employees' choice among employer-sponsored plans.
Dimension				
Financial	Premium Deductibles Coinsurance Stop-Loss	Expected Out of Pocket Cost	Price Deductible	Premium Coinsurance
Coverage	Preventive Care		Long-Term Care Outpatient Mental Health	Emergency Care Prescription Drugs Dental Care Mental Health Preventive Care Vision Care
Continuity			Choice of Physician Choice of Hospital	Choice of Physician Choice of Hospital
Convenience		Expected Travel Time		Office Hours Paperwork Travel Time Phone Consultations
Access	Appointment Waiting Time Office Waiting Time		Reputation for Waiting Times	Office Waiting Time Appointment Waiting Time

Table II.2 (Cont'd): Summary of Studies Using Multiattribute Health Plan Choice Models

Quality of Care			Reputation for Friendliness Reputation for Quality	Hospital Quality
Research Design	Non-experimental Actual Choices Nested Logit Mail Survey	Non-experimental Actual Choices Binary logit Mail Survey	Experimental Interaction Analysis Hypothetical Choices Mail Survey	Experimental Conjoint Exercise Hypothetical Choices Mail Survey
Sample	Minneapolis, MN Employees with single coverage plans (n=900) and with family coverage (n=2,100)	Carnegie-Mellon University Employees (n=242)	National Sample of Medicare Beneficiaries (n=1,161)	Maryland State Employees (n=562)
Source of Plan Attributes	Literature Review Policy Interest	Literature Review	Literature Review Policy Interest Focus Groups	Literature Review Focus Groups

Chapter IV: Model Specification and Estimation Methodology

This study addresses the omitted variable problem discussed in Chapter III by treating health plan attributes that are theoretically relevant, but unobserved, as latent variables. These latent variables are treated as model parameters to be estimated. The following section provides a verbal overview of the model specification and estimation methodology. The subsequent sections outline the health plan choice model and estimation methods formally. These sections discuss issues related to parameter identification, the interpretation of coefficient estimates, the advantage of the extended version of the heterogeneous logit model relative to a standard logit model, and the simulated maximum likelihood estimation procedure.

Overview.

In this study, quality of care and several aspects of plan convenience are assumed to be relevant to decision makers but unobserved in the Twin Cities Medicare data. Parameter estimates are used to represent the value of these unobserved attributes as perceived by the average decision maker. The approach used in this study draws heavily from the marketing research literature on multiattribute brand choice (Green and Wind, 1973) and from recent advances in econometric methods for estimating

discrete choice models (Elrod and Keane, 1994; Elrod, 1988). This new approach enables researchers to make inferences about decision makers' perceptions of plan attributes by observing (1) the plan choices of elderly decision makers and (2) a measure of the importance that decision makers place on individual plan attributes.

The important idea underlying this approach is that, given a measure of attribute importance, the researcher can learn about perceptions of that attribute by observing choice. The more importance that a decision maker places on a particular attribute, the more the decision maker will prefer the alternative that he or she perceives as offering more of that attribute.

This study uses a heterogeneous logit specification that is extended to include data about attribute importance. This specification offers several advantages. First, individual level variation in attribute importance enables the identification of perceptual parameters with cross-sectional data. To date, studies that treat unmeasured attributes as latent variables require panel data. Panel data on plan choices is costly and time consuming to collect.

Unlike the standard logit model, the heterogeneous logit model does not suffer from reliance on the restrictive assumption of independence of irrelevant alternatives (IIA). The extended heterogeneous logit allows correlation among model components that are treated

as unobserved in the standard logit. In this study, the degree of correlation, or substitution, is determined in two ways: (1) the population distribution of importance weights and (2) the relative value and covariance among the latent variables representing unobserved attributes.

The goal of the estimation procedure is to find a set of parameters that maximizes the predicted probability that each person in the data chooses the plan that they are observed to choose. To estimate the choice model parameters, the model must be written as a likelihood function comprised of individual choice probabilities. Unfortunately, the parameters in this model can not be estimated with maximum likelihood techniques. The problem is that, in this model, these choice probabilities depend on measurement error. As a result, the likelihood function contains integrals for which there are no closed form solutions. However, this likelihood function can be approximated. The approximate likelihood function can be maximized by standard gradient optimization methods. The resulting 'simulated maximum likelihood estimator' can be shown to be consistent under reasonable assumptions (Lee, 1992).

A Model of Health Plan Choice.

This study uses an extended version of a heterogeneous logit specification to statistically approximate the parameters of a multiattribute model of

health plan choice where some of the attributes relevant to decision makers are unobserved. This study extends the heterogeneous logit to include information about attribute importance. The model specification used in this study allows joint estimation of (1) the distribution of preferences across decision makers for observed attributes conditional on observing the importance that a decision maker places on particular attributes and (2) the degree of similarity among unobserved attributes as perceived by the average decision maker relative to a baseline alternative.

The health plan choice model can be written formally as follows. Let decision maker i choose the utility maximizing health plan from a mutually exclusive set of alternatives, $j = 1, \dots, J$. Define the decision maker's utility from health plan j as

$$(IV.1a) \quad v_{ij} = x'_{ij}\beta_i + u_{ij} \quad \text{where}$$

x_{ij} is a vector of alternative specific attributes of health plan j ;

β_i is a vector of individual specific preference weights corresponding to each of the attributes; and

u_{ij} is a individual-plan specific, random disturbance term representing idiosyncrasies across decision makers.

The probability that an individual chooses the j th plan equals

$$(IV.2) \quad P_i(j = 1) = P_i(u_{ik} < u_{ij} + x'_{j1}\beta_i - x'_{k1}\beta_i) \quad \text{for all } k \neq j.$$

The logit model is obtained by assuming that the u_{ij} are independent and identically distributed, following a standard extreme value distribution where

$$(IV.3a) \quad f(u_{ij}) = \exp(-u_{ij} - e^{-u_{ij}}) \text{ and}$$

$$(IV.3b) \quad F(u_{ij}) = \exp(-e^{-u_{ij}}).$$

Incorporating Unobserved Model Components. The researcher can not observe important components of the utility function. First, the researcher can not readily observe all of the attributes of health plans that are relevant to the decision maker. Partitioning equation (IV.1a) into observed and unobserved attributes,

$$(IV.1b) \quad v_{ij} = x'_{j1}\beta_{i1} + x'_{j2}\beta_{i2} + u_{ij} \quad \text{where}$$

x_{j1} is a $K \times 1$ vector of alternative-specific, observable attributes of health plan j ;

x_{j2} is a $P \times 1$ vector of alternative-specific, unobservable attributes of health plan j ;

β_{i1} is a vector of individual-specific preference weights corresponding to each of the observable attributes; and

β_{i2} is a vector of individual-specific preference weights corresponding to each of the unobservable attributes.

Second, in general, the researcher does not observe the decision maker's true preference weights. Instead, in the data set used in this analysis, the researcher observes an ordinal measure of the importance that the decision maker assigns a particular health plan attribute (1 = not important, 4 = somewhat important, 7 = very important).¹ It is this direct measure of preferences that allows the identification of perceptual parameters with cross-sectional data.

The importance weight measure can be seen as a 'noisy', or error-ridden, measure of the true, continuous preference weight. Person i 's true preference weight for attribute k can be written as a linear function of the importance measure, $s_{i,k}$, and a random error term, $\epsilon_{i,k}$

$$(IV.4a) \quad \beta_{i,k} = \alpha_{0,k} + \alpha_{1,k}s_{i,k} + \gamma_k\epsilon_{i,k}$$

where $\epsilon_{i,k} \sim N(0,1)$ and $s_{i,k} \in \{1,4,7\}$.

The conditional mean utility weight is $\alpha_{0,k} + \alpha_{1,k}s_{i,k}$ with variance $(\gamma_k)^2$. Together the parameters $\alpha_{0,k}$, $\alpha_{1,k}$ and γ_k indicate the amount of signal, or information, contained in the attribute importance measures $s_{i,k}$. A large $\alpha_{0,k}$,

¹ It is important to note that the scale used to represent the importance weight responses is arbitrary. However, the choice of scale determines the scale for the model parameters.

other things equal, indicates the importance of the overall level of the attribute in determining choice. A large $\alpha_{1,k}$, other things equal, indicates that the importance measures, $s_{i,k}$, have greater power to discriminate among different levels of underlying true preference. Finally, a large γ_k , other things equal, indicates that together $\alpha_{0,k}$ and $\alpha_{1,k}s_{i,k}$ contain relatively less information about true preferences.

Inserting the measurement equations (IV.4a) into the preference weight vectors in equation (IV.1b) and representing the unobserved attributes $x_{j,2}$ with the parameter ϕ_j yields

$$\begin{aligned} v_{i,j} &= x'_{j,1} (\alpha_{0,1} + \alpha_{1,1}s_{i,1} + \gamma_1 \epsilon_{i,1}) + \\ (IV.1c) \quad &\phi_j (\alpha_{0,2} + \alpha_{1,2}s_{i,2} + \gamma_2 \epsilon_{i,2}) + u_{i,j} \\ j &= 1, \dots, J. \quad \text{where }^2 \end{aligned}$$

$\alpha_{1,1}$ and γ_1 are $K \times K$ diagonal matrices
measurement equation parameters
corresponding to observed attributes;

$\alpha_{1,2}$ and γ_2 are $P \times P$ diagonal matrices
measurement equation parameters
corresponding to unobserved attributes;

$\alpha_{0,1}$ is a $K \times 1$ vector of measurement
equation parameters corresponding to
observed attributes;

² The observed portion of this model is similar to a heterogeneous logit model of brand choice by Gonul and Srinivasan (1993). Gonul and Srinivasan use repeat purchase data and assume that preferences are distributed multivariate normal in order to estimate heterogeneous preference parameters.

$\alpha_{0,2}$ is a $P \times 1$ vector of measurement equation parameters corresponding to unobserved attributes;

ϕ_j is a $P \times 1$ vector of parameters representing decision makers' perceptions of the value of the unobserved attributes;

$s_{i,1}$ and $\varepsilon_{i,1}$ are $K \times 1$ vectors of importance weights and measurement errors corresponding to observed attributes; and

$s_{i,2}$ and $\varepsilon_{i,2}$ are $P \times 1$ vectors of importance weights and measurement errors corresponding to unobserved attributes.

The total number of parameters in the model depends on the number of observed and unobserved attributes. The assumption that preferences vary across decision makers and the distributional assumption on the error term, $u_{i,j}$, places this model in the family of random parameter (or heterogeneous) logit models.

To summarize, the researcher observes the individual's utility maximizing choice, observable health plan attributes and attribute importance responses. The researcher does not observe either the decision maker's utility corresponding to each health plan or unobservable health plan attributes. The researcher would like to learn about the parameters $\theta = (\alpha_{0,1}, \alpha_{1,1}, \gamma_1, \alpha_{0,2}, \alpha_{1,2}, \gamma_2, \phi_j)$, as well as the probability that an individual i will choose health plan j .

Identification. Not all of the parameters of the choice model are identified. Thus, it is possible that

the same choice behavior can be generated by different parameter values. Identification requires several model restrictions. First, in order to distinguish the perceptual parameters, ϕ_j , from the measurement error parameters in equation (IV.1c), the measurement error in preference equation (IV.4a) must be normalized. This normalization is accomplished by dividing equation (IV.4a) by γ_p when attribute p is not observed.

$$(IV.4b) \quad \beta_{i,p}^* = \alpha_{0,p}^* + \alpha_{1,p}^* s_{i,p} + \epsilon_{i,p} \quad \text{where } \gamma_p \neq 0.$$

Second, it is not possible to estimate the level of decision makers' perceptions of the value of the unobserved attributes, ϕ_j , for each alternative from choice data alone. Utility differences, not absolute levels, affect choices. For this reason, it is necessary to subtract the level of unobserved attributes in one reference category, h , from each of the J utility equations in (IV.1c). After differencing, the vector of identified parameters becomes ϕ_j^* .³

Third, measurement equation parameters are identified only when there are differences in the level of the corresponding attributes across at least two alternative plans. For observed attributes, these must be differences measured by the researcher. For unobserved attributes,

³ The resulting parameters are consistent with 'similarity' parameters in the marketing literature (see Green and Wind, 1973).

these must be differences perceived by the decision makers.

Conditional on observing i 's measurement error draw, the final identified model can be written

$$(IV.1d) \quad \begin{aligned} v_{i,j} = & x'_{j,1} (\alpha_{0,1} + \alpha_{1,1} s'_{i,1} + \gamma_1 \epsilon'_{i,1}) + \\ & \varphi_j^* (\alpha_{0,2}^* + \alpha_{1,2}^* s'_{i,2} + \epsilon_{i,2}^*) + u_{i,j} \end{aligned} \quad , \quad j = 1, \dots, J$$

where $\varphi_J^* = 0$. After the identifying restrictions, the subset of parameters to be estimated can be written $\theta^* = (\alpha_{0,1}, \alpha_{1,1}, \gamma_1, \alpha_{0,2}^*, \alpha_{1,2}^*, \varphi_j^*)$.

It is worthwhile to provide the intuition behind the identification of parameters in equation (IV.1d). First, consider the $(K + P) \times 1$ vector of slope parameters, α_1 , in the preference equation (IV.4a). Greater estimated values of α_1 result from a greater consistency between sample members' attribute importance responses and the attributes of health plans. For example, greater values of $\alpha_{1, \text{premium}}$ occur when the sample members who place greater importance on low premiums are observed to choose plans with relatively low premiums.

Second, consider the $(K + P) \times 1$ vector of constants, α_0 , in the preference equation (IV.4a). Larger estimated values of α_0 arise when there is a stronger relationship in the data between the overall level of $x_{j,1}$ and φ_j^* and plan choice. In other words, α_0 measures the strength of the 'main' effect of the attributes and α_1 measures the

strength of the interaction of the attributes and the attribute importance responses.

Third, the $K \times 1$ vector γ_1 contains variance parameters in the preference equation. Greater estimated values of γ_1 result from greater heterogeneity in choice among sample members who face the same plan attributes and who report identical levels of attribute importance. Finally, the $P \times (J-1)$ matrix ϕ_j^* contains perceptual parameters representing the average perceived amount of the latent attributes in plan j . Greater estimated values of ϕ_j^* result from a stronger relationship in the sample between attribute importance responses corresponding to unobserved attributes and plan choice.

Independence of Irrelevant Alternatives. It is important to note that, unlike the standard logit model, the model specification used in this study does not suffer from a reliance on the assumption of the independence of irrelevant alternatives (IIA). Models that must satisfy the IIA assumption are limited in their ability to explain substitution and complementarity among alternatives (Maddala, 1983). IIA means that when a new alternative is added to the choice set the model makes the unrealistic assumption that decision makers will continue to choose the original alternatives at the same relative rate (Hausman and Wise, 1978). This problem is inherent in the standard logit model assumption that the alternative specific, random error components are uncorrelated and

homoskedastic. In many choice model applications, the error terms represent unobserved attributes of alternatives and individual deviations from the preferences of the average decision maker (Hausman and Wise, 1978). If these unobserved components result in error terms that are correlated across alternatives, the standard logit model would produce inconsistent estimates of choice model parameters.

The model used in this study avoids this problem by including explicitly in the model two components that, if omitted (as they would be in the standard logit model), would cause the distributional assumption in equation (IV.3b) to be violated. The first component is variation in preferences across decision makers. In this study, preferences weights are a function of the individual importance weight responses. Thus, the degree of substitution across health plans is determined, in part, by the population distribution of importance weights. Unobserved attributes comprise the second component. Heterogeneity enables the identification and estimation of parameters representing otherwise unobservable plan attributes.

Extended Heterogeneous Logit vs. Probit. The extended heterogeneous logit model is a practical alternative to the multinomial probit model (MNP). In theory, the MNP is more robust than the heterogeneous logit model to the omission of variables relevant to

health plan choice that are correlated across choices. In practice, however, identification problems limit this advantage of the MNP. Keane (1994) uses a Monte Carlo simulation to show the difficulty in estimating the parameters of the MNP model with an unrestricted variance-covariance matrix, even when the parameters are formally identified. Keane (1994) shows that fragile identification can be addressed by placing restrictions on the variance-covariance matrix. The model specification used in this study captures the effect of theoretically relevant sources of correlation across alternatives. Thus, it can be seen as equivalent to imposing a lower order factor structure on the MNP variance-covariance matrix, thereby reducing the problem of fragile identification associated with the MNP.

Simulated Maximum Likelihood Estimator.

The health plan choice model is estimated by an improved method of simulated maximum likelihood (SML) originally proposed by Lerman and Manski (1981).⁴ Erdem and Keane (1996) also use SML to estimate a type of heterogeneous logit model. Conditional on observing ϵ_i , a $(K + P) \times 1$ vector of measurement errors drawn from an

⁴ If measurement error in equation (IV.1d) is assumed to be zero, α_i^* and Φ_j^* are no longer separately identified and the model reduces to a combination of conditional and multinomial logit and can be estimated with standard maximum likelihood techniques.

i.i.d. standard normal distribution, the logit probability that an individual chooses health plan j can be written

$$(IV.5) \quad p(y_i = j | \varepsilon, \theta^*) = \frac{\exp[v_{i,j}(z'_{i,j}(\varepsilon), \theta^*)]}{1 + \sum_{l=1}^{J-1} \exp[v_{i,l}(z'_{i,l}(\varepsilon), \theta^*)]}$$

where $z_{i,j}(\varepsilon)$ is vector of explanatory variables specific to health plan j and individual i and θ^* is a vector of reduced form parameters.

The unconditional probability is obtained by integrating over all possible values of $z_{i,j}(\varepsilon)$. This integral is approximated by

$$(IV.6) \quad \hat{p}(y_i = j | \theta^*) = \frac{1}{M} \sum_{m=1}^M p(y_i = j | \varepsilon_m, \theta^*)$$

where m refers to a particular measurement error draw. The likelihood function is approximated by

$$(IV.7) \quad \hat{L}(\theta^*) = \sum_{i=1}^N \sum_{j=1}^J d_{i,j} w(j) \ln \hat{p}(y_i = j | \theta^*)$$

where $d_{i,j}$ is a variable indicating that person i chose alternative j and $w(j)$ is a weight that adjusts for over sampling in the fee-for-service sector. The derivation of the sampling weights is discussed in Appendix A. This approximation becomes more accurate as the number of draws increases. Lee (1992) shows that the SML estimator is

consistent and asymptotically normal if $\frac{M}{N^{1/2}} \rightarrow \infty$ as $N \rightarrow \infty$. Asymptotic normality of the SML estimator allows the usual specification and hypothesis tests to be applied to the resulting model parameters (See McFadden, 1973). Monte Carlo evidence shows that the SML works well as long as the simulated probabilities are smooth functions of model parameters (Geweke et al., 1994) as in the case of equation (IV.5). The SML estimates can be obtained by the gradient optimization algorithm of Berndt, Hall, Hall and Hausman (1974), otherwise known as BHHH. The estimation procedure can be summarized as follows.

1. For each of $i = 1, \dots, N$ individuals, draw $m = 1, \dots, M$ vectors of hypothetical measurement errors.
2. Pick a starting value θ^s where s denotes the estimate of θ^* at iteration s .
3. Evaluate the likelihood function shown in equation (6) at θ^s
4. Update θ^s based on $\theta^{s+1} = \theta^s - \lambda^s H^{-1} \frac{\partial L(\theta)}{\partial \theta} \Big|_{\theta^s}$.
where $H^{-1} \approx - \frac{\partial L(\theta)}{\partial \theta} \frac{\partial L(\theta)}{\partial \theta'} \Big|_{\theta^s}$ and λ^s is the step size.
5. Return to step 3. Iterate until parameter estimates converge.

Summary.

This study treats health plan attributes that are theoretically relevant, but unobserved, as latent

variables. Parameter estimates are used to represent the value of the unobserved attributes as perceived by the average decision maker. This approach enables researchers to make inferences about decision makers' perceptions of plan attributes by observing (1) the plan choices and (2) a measure of the importance that decision makers place on individual plan attributes. The idea is that, given a measure of attribute importance, the researcher can learn about perceptions of that attribute by observing choice. The more importance that a decision maker places on a particular attribute, the more the decision maker will prefer the alternative that is perceived as offering more of that attribute.

This study uses a heterogeneous logit specification that is extended to include data about attribute importance. Individual level variation in attribute importance enables the identification of perceptual parameters with cross-sectional data and allows the identification of the effect of observed plan attributes that are otherwise collinear in observational data. Also, the health plan choice model used here does not suffer from reliance on the assumption of independence of irrelevant alternatives (IIA) because it explicitly accounts for theoretically relevant sources of correlation across plans. A simulated maximum likelihood (SML) estimator is used to estimate choice model parameters.

The SML estimator is a practical means of incorporating measurement error in the importance weight responses.

Chapter V: Data Source and Empirical Specification

This chapter discusses the data source and the variables used to estimate the health plan choice model developed in Chapter IV. The following sections describe in detail the Twin Cities Medicare data set, the five plan alternatives assumed to be available to Twin Cities Medicare beneficiaries, the measure of attribute importance used to identify the perceptual parameters, and the attributes of these plans, both observed and unobserved.

Twin Cities Medicare Data.

The data used in this study come from a 1988 survey of Medicare beneficiaries living in the seven county Minneapolis-St. Paul (Twin Cities) metropolitan statistical area. The survey was conducted as part of a study of the Twin Cities Medicare health plan market conducted by the Institute for Health Services Research at the University of Minnesota. The study was funded by the Health Care Financing Administration. The Twin Cities Medicare health plan market is well suited for a study of choice among a set of plan alternatives that includes fee-for-service (FFS) and health maintenance organizations (HMOs). Unlike other health plan markets, the Twin Cities area had experience with HMO options in the 30 years preceding the study. The fact that HMO options were well established at the time of the survey increases the likelihood that respondents were familiar with

HMO options. Further, the number of HMO options and the proportion of elderly (50.4 percent) enrolled in the HMO sector gives a picture of a health plan market that may result from a number of current policy proposals aimed at increasing the role of managed care in Medicare.

The survey instrument was administered to a stratified random sample of Twin Cities Medicare Beneficiaries eligible for participation in the study. The Appendix C contains the survey instrument. To be eligible for the survey, respondents had to be over age 65, participate in both Medicare Part A and Part B, could not receive Medicaid or Supplemental Security Income benefits, and could not be a member of a Social HMO. The survey collected information about the level of importance that the respondents placed on various health plan attributes. In addition, the in-person interview collected demographic information, self-perceived health status, self-reported information on chronic conditions and physical function, and sources of influential information about health plans. Interviews were conducted between November 1987 and April 1988. FFS sector enrollees were over sampled in order to obtain more precise estimates of FFS expenditures (expenditure data is not used in this study). Appendix A discusses computation of sampling weights used to account for over-sampling of FFS enrollees in the Twin Cities data.

The study also collected information about the attributes of medigap plans held by survey respondents. When

survey respondents indicated that they held medigap plans, firms that sold those particular plans were contacted. It was not necessary to collect information about the attributes of basic Medicare and HMO plans because their attributes did not vary across individuals and attribute information was readily available from consumer guides and marketing materials.

The final response rate was 82 percent, resulting in 2,375 completed interviews. Dowd and others (1994) provide a detailed analysis of non-response in the Twin Cities data.

Non-response was more frequent among HMO enrollees and older age groups. However, the potential for non-response bias is mitigated by the lack of statistically significant differences in age, sex and residency between respondents and non-respondents in the HMO sample. The exclusion of respondents age 90 and older in this study (discussed in the next section) reduces the concern about bias resulting from disproportionate non-response among the oldest members of the sample.

Limiting Analysis to Subgroup in the Individual Market.

The parameters of the health plan choice model outlined in Chapter IV are estimated with the subsample of 1,274 survey respondents. This subsample includes respondents age 89 and younger and those who purchased plans from the individual market. The exclusion of respondents over the age

90 is a result of an administrative error at the time of data collection. As a result of this error, the survey contains no information about attribute importance for the oldest sample members.

The study is limited to those with individual plans for theoretical and practical reasons. There is reason to suspect that the observed choice behavior of those who belong to groups that sponsor health plans is not well described by the model specification outlined in Chapter IV. Instead, the choice behavior of those in groups may be best explained as the result of a joint process involving the benefits manager and the group member. Group members have the advantage of a benefits manager who shops for health plans on their behalf. As discussed in Chapter II, benefits managers have an informational advantage over individual decision makers and group plans tend to have lower premiums and offer more generous benefits than individual plans. For this reason, group members may believe that there is no benefit from shopping for individual plans on their own or even from using information to form perceptions of individual plans.

Ideally, one would like to test the hypothesis that the same choice model applies to both subgroups before making the decision to limit the analysis to a sample subgroup. Unfortunately, the Twin Cities data does not contain sufficient information to test this hypothesis. The problem is that there is a disproportionate amount of missing data pertaining to respondents with group-sponsored plans in the

data documenting the attributes of FFS supplemental plans. Because the data does not contain any information about the survey respondents' former employers there is no reliable way to impute missing attributes from sample information. Further, wide variation in the structure and cost of group-sponsored plans (See Chapter II, Footnote 2) combined with the lack of employer information makes imputation of missing attributes from outside sources an especially unreliable strategy.

The Set of Health Plan Alternatives.

The empirical specification of the health plan choice model requires some simplifying assumptions about the composition of the set of plan alternatives. In 1988 in the Twin Cities, elderly Medicare beneficiaries could choose among a set of plans that included the basic Medicare entitlement without any form of supplemental plan, five HMO plans, and FFS supplemental plans sold by hundreds of different insurers.¹ The Twin Cities data set does not contain enough information to consider each of these plans separately in estimating model parameters. Further, implicit in the model is the assumption that decision makers treat plans sold by different companies but with the same attributes values as the same plan. For this reason, plan

¹ In 1988, Medicare enrollees could enroll in two types of Network HMOs (Group Health and Medcenters) and three types of independent practice associations (HMO Minnesota, Physicians Health Plan, and Share).

types were defined by five homogeneous 'bundles' of attributes.

The five Twin Cities HMOs can be divided into two plan types distinguished by the degree of provider choice, premium level, and prescription drug coverage. Specifying a set of FFS plans that accounts for major distinguishing features is more difficult because of the greater degree of variation in plan attributes across decision makers. The first type of FFS plan is the basic Medicare entitlement. The data documenting the attributes of the FFS supplements held by survey respondents were used to create the other two other FFS plan types. The most prevalent FFS supplements fell into one of two types: (1) those that covered prescription drugs and (2) those that did not. In the Twin Cities data, plans that cover drugs have substantially higher premiums and tend not to cover care in skilled nursing facilities beyond 150 days.

Sample enrollment in each of the five plan types is listed in Table V.1. These plans are described briefly below and in more detail in a subsequent section.

Plan 1: Basic Medicare.

This option consists of the basic Medicare entitlement as described in Chapter II. Enrollees in basic Medicare are responsible for full payment of copayments and deductibles.

Plan 2: Medigap without Drug Coverage.

This option is the least expensive of the two FFS supplemental plans. These plans are more likely to cover some post-acute care in skilled nursing facility beyond the basic Medicare entitlement.

Plan 3: Medigap with Drug Coverage.

This option covers prescription drugs and is substantially more expensive. These plans are less likely to cover post-acute care in skilled nursing facility beyond the basic Medicare entitlement.

Plan 4: Independent Practice Associations.

IPAs are a type of HMO that contracts with a large number of independent providers allowing enrollees relatively wide choice of provider and hospital. In the Twin Cities in 1988, IPA options did not cover prescription drugs, nor did IPAs cover post-acute care in a skilled nursing facility beyond the basic Medicare entitlement.

Plan 5: Network HMOs.

Network HMOs are a form of HMO that contracts with a single multispecialty physician group. Relative to IPAs, Network HMOs place greater restrictions on enrollees' choice of provider and hospital. In the Twin Cities in 1988, Network HMOs covered prescription drugs but did not cover

post-acute care in a skilled nursing facility beyond the basic Medicare entitlement.

Attribute Importance.

The choice model developed in Chapter IV assumes that decision makers view their health plan alternatives as 'bundles' of attributes. In the Twin Cities survey, respondents were asked to rate the importance of fifteen specific attributes in the context of having to choose a health plan (The attribute 'does not matter' to the respondent; the respondent would 'like to have' the attribute; or the respondent 'has to have' the attribute; See survey question 26 in Appendix C). Table V.2 lists these attributes. Attributes correspond to premiums, cost sharing, covered services, paperwork burden, and convenience. Attributes corresponding to the degree of provider choice and the ease of referral to specialists refer to access to services. 'Being rushed from the hospital' refers to process of care. The final attribute corresponds to overall quality of care in the health plan. As discussed earlier, quality of care is not a clearly defined concept. Thus, it is not certain what aspects of quality survey respondents have in mind when they answer this question. However, evidence from focus groups suggests that in defining quality, consumers tend to emphasize the interpersonal aspects of care over technical measures of process and outcome (Agency for Health Care Policy and Research, 1994; Lohr, 1990).

In this analysis, the attribute importance responses are used as a measure of sample members' true preferences. There are two important assumptions implicit in using the attribute importance measure in this way. The first assumption is that the attribute importance responses are exogenous. In other words, the sample members, plan choices do not influence their importance responses. The second is that the set of attributes included in the survey was the same set of alternatives that determined the current enrollment choice. Unfortunately, these two assumptions are not testable given the cross-sectional nature of the data.

Table V.2 lists the proportion of sample members responding at each level of importance for all fifteen plan attributes. In general, respondents placed the greatest importance on attributes related to access and quality of care. Attributes related to cost and coverage were rated second in importance. The respondents rated attributes related to convenience (with the exception of paperwork burden) as less important than attributes related to cost, paperwork, covered services and quality of care. Respondents also placed greater importance on choice of physician than on choice of hospital. The location of clinics and doctors offices was considered more important than the hours of operation. Finally, the waiting time to get an appointment was considered more important than time spent waiting in the office or clinic to see the provider.

The estimation of choice model parameters depends in part on the relationship between the importance weight responses and plan choices. Simple visual comparisons reveal relationships between plan choice and attribute importance related to quality of care and financial aspects of plans. These relationships are not as evident for attributes related to convenience. The relationship between attribute importance and plan choice can be shown compactly by treating ordinal importance as an interval measure, calculating the mean level of importance, and ranking the resulting means. Table V.3 shows the mean level of importance and rankings for the combined sample and the sample divided into subgroups on the basis of plan enrollment. Enrollees in basic Medicare placed greater importance on premiums and cost sharing than did enrollees in the other four plans. HMO enrollees placed greater importance on the coverage of preventive care and low paperwork burden compared to enrollees in other plans. Network HMO enrollees placed the least importance on choice of physician and hospital. With the exception of enrollees in basic Medicare, respondents who place greater importance on drug coverage are enrolled in plans that offer this benefit. Finally, the simple comparison of mean responses and ranks does not reveal a strong relationship between attributes related to convenience and plan choice.

Again, the purpose of the importance measures is to control for differences in decision makers' 'tastes' or preferences for health plan attributes. The importance

weights are a more valid or 'believable' measure of preferences, if the responses vary across subgroups of decision makers in a manner suggested either by the literature on health plan choice or intuition. In order to assess the ability of the importance weights to capture differences in preferences across decision makers, the sample was divided into a number of different subgroups of policy interest. Table V.4 shows the mean level of attribute importance and rankings of the resulting means for each of the subgroups. In general, attribute importance levels and rankings vary across subgroups in expected ways.

Health Status. The sample was split into two groups on the basis of health status. Those reporting more than four health conditions² or those who report being in 'fair' or 'poor' health are considered to suffer from health problems. The two subgroups place similar levels of importance on attributes related to quality of care. Relative to the healthy subgroup, the unhealthy subgroup places greater importance on low premiums, low cost sharing and drug coverage.

² See survey question 31 in Appendix C for the list of health conditions. The health conditions with higher one-year mortality rates were assigned higher weights. These weights were roughly based on those recommended by Charlson and others (1987). Conditions with weight = 1 were high blood pressure, diabetes, arthritis or rheumatism, mental problems, heart trouble or angina, digestive problems, such as ulcers, gall bladder trouble or colitis, Alzheimer's disease and circulation problems or hardening of the arteries. Conditions with weight = 2 were tumors or cancer other than skin cancer, paralysis effects of stroke, and kidney or bladder problems. Conditions with weight = 3 were liver problems such as cirrhosis. Conditions that were assigned a weight = 0 were speech problems, hearing problems and chronic skin problems.

Old vs. Young. The sample was split into two groups on the basis of age. Those younger than the sample median age of 74 were placed in the younger subgroup. Dividing the sample by age is a way of capturing the interaction between health status and economic well being because older groups are less healthy and have lower incomes. The two age groups share similar attribute rankings. However, the younger age group places more importance on virtually every attribute with the exception of low premiums and location. This pattern may suggest age differences in the willingness to respond in the 'must have' category that are unrelated to true underlying preferences.

Upper vs. Lower Income. The sample was split into two groups on the basis of income. Those whose annual income was greater than the sample median \$15,154 were placed in the upper income subgroup. Relative to the upper income subgroup, the lower income subgroup places greater importance on low premiums and low cost sharing, location, and drug and eyeglass coverage. At the same time, the lower income subgroup places lesser importance on quality of care and referral to specialists.

A principal components analysis was performed on the fifteen importance measures. Principal components is a technique that can be used to identify a smaller number of underlying dimensions or factors needed to explain the relationships among the set of importance weight measures (Nunnally and Bernstein, 1994). The principal components

analysis suggested that there were four orthogonal dimensions underlying the importance weight measures Table V.5 lists the loadings associated with each of the four underlying factors. In general, these dimensions are consistent with the dimensions identified in the literature on consumer satisfaction with medical care (Pascoe, 1983; Ware et al., 1983) and consumer perceptions of quality (Agency for Health Care Policy and Research, 1994; Lohr, 1990).

Two of the four importance dimensions are readily interpretable as the importance of financial aspects of plan and quality of care. Importance of premiums, cost sharing, and covered services load on the financial dimension. The importance of provider choice, quality of care, not being rushed to the hospital and referral to specialists load on a general quality of care dimension. The interpretation of the second two dimensions is less straight forward, though they appear to be related to different aspects of the importance of plan convenience. One of the two convenience factors is related to the importance of clinic and office waiting time and appointment waiting time. The second of the two convenience factors is related to the importance of the paperwork burden associated with the plan and the importance of clinic and office location and hours.

Observed Attributes.

Eight of the fifteen attributes for which importance ratings were solicited are observed in the study: (1)

premiums, (2) cost sharing, (3) drug coverage, (4) choice of hospital, (5) choice of physician, (6) coverage of preventive care, (7) coverage of eyeglasses, and (8) paperwork requirements (See Table V.6). Cost sharing is measured by the dollar value of deductibles and coinsurance associated with Medicare covered services. The dollar value of deductibles and copayments interacted with the corresponding importance weight can be seen as a proxy for the utility of expected overall expenditures associated with each plan. There are six measures of cost sharing. The Part A deductible, the 90 day hospital coinsurance, the 150 day hospital coinsurance and the Part B deductible are measured in continuous dollar terms. Plan coverage of physician charges beyond what Medicare deems usual and customary and plan coverage of care in a skilled nursing facility beyond the Medicare entitlement are represented by dichotomous variables.

All eight attributes for basic Medicare and the two HMO plans are obtained from the Medicare Handbook (U. S. Department of Health and Human Services, 1994) and from marketing materials supplied by the HMOs to prospective enrollees. Table V.6 lists the attributes of basic Medicare and the HMO plans. The specification of the attributes of the two FFS supplemental plans is less straight forward. This is because the attributes of FFS supplements related to premiums, coverage, and cost sharing can vary substantially across individual respondents.

In this analysis, a number of simplifying assumptions are made about the nature of the non-financial attributes of the two FFS supplements. These assumptions are supported by the literature on retiree health insurance discussed more fully in Chapter II. This study assumes that FFS supplemental plans do not cover preventive care, allow unrestricted choice of both hospital and physician, do not cover eyeglasses and require enrollees to submit claims for reimbursement after fulfilling the plan deductible.

Three types of missing data problems must be solved in specifying the premiums and cost sharing requirements of medigap plans. The first problem is common in studies that specify multiattribute choice models with observational data. While the Twin Cities survey collected information about medigap plans that were chosen by respondents, the survey did not collect information about the attributes of medigap plans that were in the respondent's choice set but were not chosen. This study addresses this problem by assigning the attributes of 'prototype' medigap plans to the medigap plans not chosen (or when attributes of FFS plans are totally missing). These prototypes were based on the two most frequently held medigap plans observed in the Twin Cities data. Table V.6 lists the attributes of the medigap prototypes. The first prototype is based on a Minnesota Blue Cross-Blue Shield plan sold in the Twin Cities at the time of the survey. This type of plan was held by 33 percent of survey respondents who reported enrollment in a medigap plan

with drug coverage. This plan covered outpatient prescription drugs but did not cover care in a skilled nursing facility beyond the Medicare entitlement. The second prototype plan is based on a medigap plan sold by the American Association of Retired Persons that did not cover drugs and did cover some care in skilled nursing facilities beyond Medicare ("Beyond Medicare", 1989). This type of plan was held by 22 percent of survey respondents who reported enrollment in a medigap plan without drug coverage.

The use of prototype plans as proxies for unobserved alternatives in the choice set is based on the assumption that decision makers view the prototypes as alternatives to their chosen plans. This assumption is not testable with the Twin Cities data. However, this assumption is made plausible by the fact that these plans were the most popular medigap plans in the Twin Cities data, that the prototypes are similar to popular plans reviewed by Consumer Reports in 1989, and that the American Association of Retired Persons plan was widely marketed in magazines aimed at elderly consumers ("Beyond Medicare", 1989).

The second problem results from item non-response in the part of the survey that asked health plan managers about the attributes of medigap plans held by survey respondents. The nature of the missing data problem and the strategy used to impute the missing data are described in greater detail in Appendix B. In essence, when the attributes are partially missing the data is imputed from like plans, matched on the

basis of company name and other attributes. When the attributes are totally missing the attributes of 'prototype' medigap plans are assigned. This procedure reduces overall variation in the medigap attributes. The result artificially reduces the standard error estimates corresponding to the model parameter estimates. The danger is that the null hypothesis of no effect will be rejected inappropriately.

The third problem is that the survey contained no usable premium data. This resulted from a miswording of the question in the survey that elicited medigap plan premiums. Insurers reported total premium income from a particular plan, rather than the premium that individual plan holders pay on a monthly basis. Fortunately, premium information was available from the Minnesota Department of Commerce. Appendix B discusses the source of premium data in more detail. Table V.7 lists descriptive statistics for observed FFS plans.

Latent Attributes. There are seven health plan attributes for which importance ratings are solicited but are not observed in the Twin Cities data. Unobserved attributes include the (1) quality of care, (2) the degree to which plans 'rush' enrollees from the hospital, (3) the willingness of plan providers to refer enrollees to specialists, (4) the convenience of clinic hours, (5) the convenience of clinic location, (6) the amount of time that enrollees must wait in the clinic to see providers, and (7) the time enrollees must wait for appointments. These seven comprise the set of

possible latent attributes that can be included in the analysis. The principal components analysis discussed above suggests that the seven unobserved attributes 'load' onto two underlying factors related to convenience and quality of care.

Summary.

This study uses data from a 1988 survey of Twin Cities Medicare beneficiaries who report enrollment in a health plan sold on the individual plan market. Sample members are assumed to choose among five types of health plans: (1) the basic Medicare entitlement, (2) a medigap plan that covers prescription drugs, (3) a medigap plan that does not cover prescription drugs, (4) an independent practice association, and (5) a network HMO. The Twin Cities survey inquired about the importance of fifteen plan attributes. Seven of these attributes are unobserved in the data but assumed to be relevant to decision makers in making a health plan choice. In this analysis, the attribute importance measures are important for identifying the value of the perceptual parameters representing the unobserved attributes. A simple descriptive analysis suggests that the attribute importance measures vary in expected ways across plan choices and across policy relevant subgroups.

Table V.1: Sample Plan Enrollment by Plan Type

Plan	Sample Enrollment
Basic FFS Medicare without a supplement	163
Medigap with Rx drug coverage	161
Medigap without Rx	210
IPAs	276
Network HMOs	464
Total	1274

Table V.2: Proportion of Sample Members Responding at Each Level of Attribute Importance (n = 1,274)

Plan Attributes Contained in Twin Cites Survey	... doesn't matter.	Like to have ...	Have to have ...
Low premiums	17.8	59.2	23.0
Low cost sharing	9.3	59.7	31.0
Prescription drug coverage	17.7	60.2	22.1
Eyeglass coverage	23.1	63.0	14.0
Preventive care coverage	12.6	55.3	32.0
Choice of physician	10.2	55.3	34.5
Choice of hospital	13.8	60.4	25.8
Overall Quality of Care	4.4	51.6	44.0
Referrals to specialists	4.6	54.2	41.2
Not being rushed from hospital	10.8	56.4	32.8
Paperwork burden	9.1	53.1	37.8
Clinic/office location	8.6	63.7	27.8
Clinic/office hours	14.9	69.2	15.9
Clinic/office wait	17.7	71.8	10.5
Waiting time for appointment	14.2	70.2	15.8

Table V.3: Means and Ranks of Attribute Importance Ratings
for Total Sample and by Plan Enrollment

	Total Sample n = 1274		Basic Medicare n = 163		Medigap w/o Rx n = 161		Medigap w/ Rx n = 210		IPA n = 276		Network n = 464	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Quality of care	5.189	1	4.975	2	5.304	3	5.400	1	5.196	1	5.125	1
Referrals to specialists	5.097	2	4.791	4	5.398	2	5.200	3	5.054	2	5.080	2
Paperwork burden	4.859	3	4.331	10	5.025	4	4.800	6	4.989	3	4.938	3
Physician Choice	4.728	4	4.294	7	5.509	1	5.257	2	4.978	4	4.220	10
Not being rushed from hospital	4.659	5	4.497	8	4.839	5	4.929	4	4.641	6	4.543	7
Cost sharing	4.652	6	5.160	1	4.484	7	4.314	9	4.391	9	4.841	5
Preventive care coverage	4.582	7	4.258	11	4.168	9	4.214	10	4.739	5	4.912	4
Clinic/office location	4.577	8	4.442	6	4.522	6	4.443	7	4.511	8	4.744	6
Hospital Choice	4.360	9	4.479	9	4.950	4	4.843	5	4.522	7	3.800	14
Low premium	4.155	10	4.994	3	3.963	10	3.843	14	3.717	13	4.330	8
Drug Coverage	4.130	11	4.497	5	3.870	9	4.371	8	3.717	13	4.226	9
Appointment wait	4.047	12	3.982	12	4.205	8	4.100	11	4.043	11	3.994	13
Clinic/office hours	4.031	13	3.834	14	3.963	10	4.086	12	4.054	10	4.084	11
Clinic/office wait	3.786	14	3.577	15	3.963	10	3.900	13	3.717	13	3.787	15
Eyeglass coverage	3.727	15	3.926	13	3.404	11	3.586	15	3.630	12	3.890	12

Note: 1 = the attribute 'does not matter' to the respondent,
4 = the respondent would 'like to have' the attribute, and
7 = the respondent 'has to have' the attribute.

Table V.4: Means and Ranks of Attribute Importance Ratings by Subgroup Membership

	Health Problems n=438		No Health Problems n=836		Old n=568		Young n=706		Upper Income n = 719		Lower Income n = 555	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Quality of care	5.068	1	5.252	1	4.850	1	5.461	1	5.356	1	4.973	2
Referrals to specialists	4.979	2	5.159	2	4.850	1	5.296	2	5.273	2	4.870	3
Paperwork burden	4.911	4	4.833	3	4.681	3	5.003	3	4.943	3	4.751	5
Physician Choice	4.774	5	4.703	4	4.570	4	4.833	4	4.897	3	4.508	9
Not being rushed from hospital	4.699	7	4.639	5	4.570	4	4.731	6	4.688	4	4.622	7
Low cost sharing	4.932	3	4.506	7	4.533	5	4.748	5	4.346	6	5.049	1
Preventive care coverage	4.630	8	4.556	6	4.491	6	4.654	8	4.630	5	4.519	8
Clinic/office location	4.753	6	4.484	8	4.782	2	4.656	7	4.526	5	4.648	6
Hospital Choice	4.329	11	4.377	9	4.312	7	4.399	9	4.413	7	4.292	11
Low premiums	4.452	10	4.000	12	4.211	8	4.110	10	3.762	11	4.836	4
Drug Coverage	4.562	9	3.903	13	4.079	10	4.167	11	3.962	9	4.346	10
Appointment wait	4.068	12	4.036	10	4.088	9	4.012	12	4.084	8	4.000	13
Clinic/office hours	4.027	13	4.032	11	3.989	11	4.064	12	4.033	10	4.027	12
Clinic/office wait	3.740	15	3.810	15	3.772	12	3.796	14	3.829	12	3.730	15
Eyeglass coverage	3.911	14	3.630	14	3.667	13	3.774	15	3.608	13	3.881	14

Note: 1 = the attribute 'does not matter' to the respondent,
 4 = the respondent would 'like to have' the attribute, and
 7 = the respondent 'has to have' the attribute.

Table V.5: Rotated Factor Scores and Interpretation of
Extracted Factors from Principal Components Analysis Applied
to Attribute Importance Scores

Plan Attributes Contained in Twin Cities Survey	Factor 1: Quality of Care	Factor 2: Financial Aspects	Factor 3: Conven- ience 1	Factor 4: Conven- ience 2
Premiums	-0.0319	0.7333	0.1184	-0.0161
Cost sharing	0.0558	0.7268	0.2357	-0.1202
Coverage of prescription drugs	0.1551	0.6653	-0.0648	0.2023
Coverage of eyeglasses	0.0204	0.6170	0.0443	0.2295
Coverage of preventive care	0.2314	0.3767	0.4155	0.0901
Choice of physician	0.8064	-0.0073	0.0516	0.1493
Choice of hospital	0.7720	0.06121	-0.0757	0.1387
Overall Quality of Care	0.6330	0.0082	0.4516	0.0157
Referrals to specialists	0.6363	0.0427	0.3954	0.0476
Not being rushed from the hospital	0.6136	0.1952	0.2236	0.1218
Paperwork burden	0.3193	0.0877	0.5934	-0.0533
Clinic/office location	0.1085	0.1479	0.7439	0.1558
Clinic/office hours	-0.1833	0.04271	0.6489	0.3845
Clinic/office wait	0.1217	0.1173	0.1335	0.8309
Waiting time for appointment	0.2390	0.11668	0.1624	0.7677

Note: Factor loadings of 0.4000 or greater are displayed in bold.

Table V.6: Observed Attributes in Basic Medicare and Twin Cities HMO and FFS Prototypes

Attribute Importance Indicators	Observed Attribute	Basic Medicare	Prototype Medigap w/o Rx	Prototype Medigap w/ Rx	IPA	Network
Premium	Monthly premium	\$28	age 65-69 \$71 70-74 \$75 75+ \$82	age 65-69 \$95 70-74 \$102 75+ \$109	\$53	\$40
Out-of-pocket costs	Hospital deductible	\$540	\$0	\$0	\$0	\$0
	Hospital 61-90 day coinsurance	\$75	\$200	\$200	\$0	\$0
	Hospital 91-150 day coinsurance	\$135	\$0	\$0	\$0	\$0
	Physician deductible	\$270	\$0	\$0	\$0	\$0
	Covers excess charges (1,0)	0	0	0	1	1
	Covers SNF beyond MCARE (1,0)	0	1	0	0	0
Drug coverage	Covers out-patient Rx (1,0)	0	0	1	0	1
Eyeglass coverage	Covers eye glasses (1,0)	0	0	0	0	1
Preventive care coverage	Covers preventative care (1,0)	0	0	0	1	1
Choice of hospital	Permits choice of hospital (1,0)	1	1	1	1	0
Choice of MD	Permits choice of MD (1,0)	1	1	1	1	0
Paperwork burden	Submit claim for reimbursement (1,0)	1	1	1	0	0

Table V.7: Mean and Standard Deviation of Attributes in Medigap Plans

Attribute Importance Indicators	Observed Attribute	Medigap w/o Rx	Medigap w/ Rx
		n = 161	n = 210
Premium	Monthly premium	\$77.32 (11.25)	\$104.41 (13.90)
Out-of- pocket costs	Hospital deductible	\$6.42 (54.00)	\$16.03 (81.90)
	Hospital 61- 90 day coinsurance	\$1.13 (11.62)	\$0.97 (12.95)
	Hospital 91- 150 day coinsurance	\$2.77 (24.16)	\$2.39 (26.63)
	Physician deductible	\$185.42 (47.51)	\$183.23 (51.00)
	Covers excess charges (1,0)	0.05 (0.71)	0.05 (0.23)
	Covers SNF beyond MCARE (1,0)	0.96 (0.21)	0.07 (0.25)

Note: Negative deductibles and coinsurance result when survey respondents report ownership of hospital indemnity plans as medigap plans. See Appendix B for details.

Chapter VI: Empirical Findings

This chapter presents results from an empirical test of the choice model developed in Chapter IV using the Twin Cities Medicare data discussed in Chapter V. Overall, the findings suggest that the elderly perceive the quality of care in HMO plans as being lower than that offered by traditional medigap plans. This finding is consistent with the fears about the quality of care in HMOs raised by consumer advocates, policy makers and researchers. An unexpected finding is that the Twin Cities elderly appear to perceive the quality of care in basic Medicare as being lower than in the other four supplemental plans. The findings also suggest that the failure to control for theoretically relevant but unobserved attributes may lead to misleading inferences about the effect of observable attributes on choice. The addition of the latent attributes to the model has the greatest impact on the importance of premiums and of attributes traditionally associated with HMO plans.

These results can also be used to simulate the effect of information about quality of care on choice probabilities. The results suggest that information about quality has a large effect on choice within the HMO sector. The effect of the information on overall enrollment in the HMO sector depends heavily on assumptions about the impact of information on perceptions of quality of care within the FFS sector.

The following sections discuss these findings in more detail. The first section discusses the steps involved in selecting a final model specification. The second section discusses the parameter estimates in the final version of the model that includes two latent attributes representing consumers' perceptions of quality of care and convenience. The third section assesses the validity of the perceptual parameter estimation approach by comparing estimates of decision makers' perceptions of premiums to actual premiums. The fourth section assesses the impact of omitting latent attributes on inferences about the effect of observable attributes. The fifth section discusses the ability of the model to capture meaningful differences across subgroups of decision makers. The final section uses the resulting parameter estimates to simulate the effect on choice of an imaginary intervention that influences consumers' perceptions of quality of care across plans.

Model Selection.

The Twin Cities data did not contain enough information to estimate all of the parameters in the fully specified model containing all seven possible latent attributes.^{1,2} For this reason, it was necessary to settle on parameter restrictions that result in an estimable model specification that maintains the ability of the analysis to address the research questions presented in Chapter I. One restriction

¹ See Equation (IV.1d) in Chapter IV.

² The SML estimator does not converge when applied to the full model.

was to assume that the constant terms in the preference equations (IV.4b) are equal to zero. In addition, two types of exploratory analysis were performed in order to settle upon additional restrictions. The goal of the first analysis was to determine the dimensionality of latent attributes. The goal of the second analysis was to determine the impact of assumptions about measurement error in importance weights on goodness of fit and on the substantive and statistical significance of the parameter estimates.

Restricting Preference Equation Constants. The small number of response categories in the attribute importance measures contributed to collinearity between the main effect of the level of the attribute and the interaction effect of the attribute and the attribute importance response. This collinearity made it difficult to separately estimate the constant and slope parameters in the preference equation (IV.4b). For this reason, the constant terms are restricted to zero. Ideally, a data set would contain a sufficiently large sample to test this restriction empirically. The assumption implicit in this restriction is that plan attributes influence utility only through their interaction with the attribute importance response. This restriction is also equivalent to assuming that the attribute importance measures contain meaningful information about preferences.

Number and Interpretation of Latent Attributes. A smaller version of the model that assumed no measurement

error in the importance weights was estimated with standard maximum likelihood techniques to determine the dimensionality of the latent attributes in the final model specification. This was done by comparing goodness of fit and the statistical significance of perceptual parameter estimates across several different model specifications. The first model contained no latent attributes.

Model 1: Observed attributes only.³

$$V_{i,j} = x_{j,1}(\alpha_1 s_{i,1}) + x_{j,2}(\alpha_2 s_{i,2}) + \dots + x_{j,13}(\alpha_{13} s_{i,13}) + u_{i,j}, \quad j = 1 \dots J.$$

The second model contained perceptual parameters representing the level of all seven possible latent attributes in each health plan.

Model 2: Observed attributes plus seven latent attributes.^{4,5}

$$V_{i,j} = x_{j,1}(\alpha_1 s_{i,1}) + x_{j,2}(\alpha_2 s_{i,2}) + \dots + x_{j,13}(\alpha_{13} s_{i,13}) + \phi_{j,1}^{**}(\tilde{s}_{i,1}) + \phi_{j,2}^{**}(\tilde{s}_{i,2}) + \phi_{j,3}^{**}(\tilde{s}_{i,3}) + \phi_{j,4}^{**}(\tilde{s}_{i,4}) + \phi_{j,5}^{**}(\tilde{s}_{i,5}) + \phi_{j,6}^{**}(\tilde{s}_{i,6}) + \phi_{j,7}^{**}(\tilde{s}_{i,7}) + u_{i,j}$$

³ Utility function elements are defined in Chapter IV, unless otherwise noted. Note that the subscript on the slope parameter in the preference equation has been removed.

⁴ $\tilde{s}_{i,1}$ = Importance of not being rushed from hospital; $\tilde{s}_{i,2}$ = Importance of referrals to specialists; $\tilde{s}_{i,3}$ = Importance of quality of care; $\tilde{s}_{i,4}$ = Importance of office location; $\tilde{s}_{i,5}$ = Importance of office hours; $\tilde{s}_{i,6}$ = Importance of appointment wait; and $\tilde{s}_{i,7}$ = Importance of office wait.

⁵ If measurement error is assumed to be zero, α_j^* and ϕ^* are no longer separately identified and the model reduces to a combination of conditional and multinomial logit and can be estimated with standard maximum likelihood techniques.

$$V_{i,j} = x_{j,1}(\alpha_1 s_{i,1}) + x_{j,2}(\alpha_2 s_{i,2}) + \dots + x_{j,13}(\alpha_{13} s_{i,13}) + u_{i,j}$$

where $\varphi_{j,p}^{**} = \varphi_{j,p}^* \alpha_p^*$, $j = 1, \dots, J-1$, and $p = 1, \dots, 7$.

A likelihood ratio test (Chi-square = 168, degrees of freedom = 28) rejects Model 1 as a restriction on Model 2 (See Table VI.1). The rejection of this restriction serves as evidence of the importance of the set of latent attributes in explaining the choice behavior observed in the sample. However, the perceptual parameter estimates corresponding to the latent attributes in Model 2 are not individually statistically significant (See Table VI.2). One explanation for the lack of individual significance may be that the attribute importance measures contain redundant information. In other words, a smaller number of latent attributes can be used to explain choice behavior observed in the sample.⁶

This explanation makes sense on theoretical grounds since four of the seven latent attributes are related intuitively to convenience and three are related intuitively to process and access dimensions of quality of care. The results of the principal components analysis discussed in the previous chapter provide empirical support for the idea of a smaller number of attributes. Recall that the analysis suggested that there were three independent dimensions underlying the importance measures corresponding to latent

⁶ A similar theoretical justification for collapsing the set of attributes is given by Prasad and Javalgi (1992).

attributes, one related to the overall quality of care and two related to different facets of convenience.

Thus, on conceptual grounds, a more compact version of the model (Model 3) was estimated that included two latent attributes corresponding to quality of care and one corresponding to convenience. The number of latent attributes in the model can be reduced by restricting the perceptual parameter estimates to be equivalent for particular attributes. Mechanically, these restrictions are imposed by creating summary measures of the importance of each of the two dimensions. This in effect forces the perceptual parameter to be the same for each of the elements of the summary measure.⁷

Model 3: Observed attributes plus two latent attributes.

$$V_{i,j} = x_{j,2}(\alpha_1 s_{i,1}) + x_{j,2}(\alpha_2 s_{i,2}) + \dots + x_{j,13}(\alpha_{13} s_{i,13}) + \phi_{j,q}^{**}(\tilde{s}_{i,q}) + \phi_{j,c}^{**}(\tilde{s}_{i,c}) + u_{i,j}$$

$$V_{i,J} = x_{J,1}(\alpha_1 s_{i,1}) + x_{J,1}(\alpha_2 s_{i,2}) + \dots + x_{J,13}(\alpha_{13} s_{i,13}) + u_{i,J}$$

where $j = 1, \dots, J-1,$

$$\phi_{j,p}^{**} = \phi_{j,p}^* \alpha_p^*,$$

$$\tilde{s}_{i,q} = \tilde{s}_{i,1} + \tilde{s}_{i,2} + \tilde{s}_{i,3}, \text{ and}$$

$$\tilde{s}_{i,c} = \tilde{s}_{i,4} + \tilde{s}_{i,5} + \tilde{s}_{i,6} + \tilde{s}_{i,7}.$$

⁷ Unit weights were assigned to each item, rather than factor loadings on the basis of parsimony. This is because the two weighting schemes produced equivalent results.

A likelihood ratio (Chi-square = 18, degrees of freedom = 16) test fails to reject Model 3 as a restriction on Model 2. Relative to the alternative specification, more of the perceptual parameter estimates in Model 3 are statistically significant (See Table VI.1 and Table VI.2). Further, collapsing the latent attributes from seven to two does not affect the values and statistical significance of the preference parameter estimates corresponding to observed attributes (See Table VI.1). On this basis, the final version of the choice model contains two composite attributes, one related to convenience and the other related to quality of care.

Measurement Error in Importance Weights. The model presented in Chapter IV treats the importance weights as an error-ridden measure of decision makers' true underlying preference for individual attributes. It is important to assess robustness of the results to assumptions about the presence of measurement error. It can be shown that in linear regression models with one explanatory variable, random measurement error causes parameter estimates to be attenuated, or smaller than their true values (Greene, 1990). Unfortunately, there are no clear predictions about the effect of measurement error in more complicated models (Greene, 1990), such as the health plan choice model estimated here. At the same time, model specifications that do not include measurement error can be estimated with commercial software. If the results from models with and

without measurement error do not yield substantively different results, it makes sense from a practical perspective to estimate the model with the computationally less costly maximum likelihood estimator.

Two different model specifications are compared in order to assess the impact of ignoring measurement error in the importance measures. A likelihood ratio test is used to test Model 3 which does not include measurement error (discussed above) as a restriction on Model 4 which does include measurement error.

Model 4: Non-zero measurement error in importance weights.⁸

$$V_{i,j} = x_{j,2}(\alpha_1 s_{i,1} + \gamma_1 \epsilon_{i,1}) + x_{j,2}(\alpha_2 s_{i,2} + \gamma_2 \epsilon_{i,2}) + \dots + \\ x_{j,13}(\alpha_{13} s_{i,13} + \gamma_{13} \epsilon_{i,13}) + \\ \Phi_{j,Q}^*(\tilde{s}_{i,Q} + \epsilon_{i,14}) + \Phi_{j,C}^*(\tilde{s}_{i,C} + \epsilon_{i,15}) + u_{i,j}$$

$$V_{i,J} = x_{J,1}(\alpha_1 s_{i,1} + \gamma_1 \epsilon_{i,1}) + x_{J,1}(\alpha_2 s_{i,2} + \gamma_2 \epsilon_{i,2}) + \dots + \\ x_{J,13}(\alpha_{13} s_{i,13} + \gamma_{13} \epsilon_{i,13}) + u_{i,J}$$

where $j = 1, \dots, J-1$.

This test rejects Model 3 as a restriction on Model 4 (Chi-square = 34, degrees of freedom = 3). This rejection suggests that measurement error is important for explaining choice behavior observed in the sample. Comparing the

⁸ Although formally identified, α_j^* and ϕ_j^* were not separately estimable with the Twin Cities data. For this reason, the preference parameters contained in the vector α_j^* associated with unobserved quality and convenience are restricted to 1.00 in Model 1 and Model 2.

parameter estimates from Model 3 and Model 4 provides evidence that ignoring measurement error results in attenuation bias (See Table VI.3 and Table VI.4). With the exception of preference parameter corresponding to premiums the parameter estimates from Model 3 are lower than those resulting from Model 4.

The inclusion of measurement error makes a difference in the substantive interpretation of some of the parameter estimates. In the case of premiums, the inclusion of measurement error helped to eliminate the perverse finding that increasing premiums increases utility. The preference parameter corresponding to premiums was reduced by a factor of five from 0.0020 (significant) to 0.0004 (not significant).

The addition of measurement error had a large impact on several of the preference equation parameters corresponding to covered services and paperwork burden. Adding measurement error also increased the preference parameter corresponding to coverage of extra skilled nursing care from 0.3877 to 0.6484. Adding measurement error increased the preference parameter corresponding to preventive care from 0.2482 to 0.4135. Finally, in the case of the requirement that enrollees submit claims for reimbursement, the preference parameter decreased from -0.0842 to -0.1610.

The exclusion of measurement error led to substantial differences in the predictions of the impact on choice probabilities from adding or removing these three services

from health plans (See Table VI.5). Excluding measurement error from the model reduced the estimated impact on choice probabilities of extra care in a skilled nursing facility as much as 11 percent. Excluding measurement error from the model reduced the predicted effect of preventive care coverage on choice by as much as nine percent. Excluding measurement error from the model reduced the predicted impact of the submission of claims requirement by as much as 10 percent.

Finally, the addition of the measurement error also increases the size of each of the perceptual parameter estimates. However, these parameter estimates are not measured according to a meaningful scale. For this reason, the effect of measurement error on the relative size of estimates is more important than their actual value in interpreting the parameter estimates. Table VI.4 shows that adding measurement error to the model does not substantially change the relative size of the perceptual parameter estimates.

These findings suggest that if the goal of the research is to estimate the impact of observable attributes on choice, then it is important to model measurement error generated by measuring continuous preferences ordinally. However, if the goal is to estimate perceptual parameters controlling for observable attributes, then including measurement error in the choice model is less important.

Final Model Results.

The final model (Model 4) specification contains perceptual parameters representing the value of perceived quality of care and perceived convenience in each health plan (See Table VI.3 and Table VI.4). The final model also accounts for error in the importance weight responses.

Preference Equation Estimates. In the final model, the small value of the premium coefficient (0.0004) is not significantly different from zero, suggesting that the Twin Cities elderly are not sensitive to premium levels in choosing a health plan.^{9,10} However, data limitations should be considered before concluding that premiums play no role in plan choices, because this data does not provide a test of the independent effect of premium on plan choice. This is because premium and plan coverage are highly correlated in the Twin Cities data.¹¹

⁹Marginal plan choice probabilities with respect to \$1.00 change in "own" premium:

Basic Medicare = -4.27×10^{-4} ,
Medigap without drugs = 8.84×10^{-4} ,
Medigap with drugs = 1.28×10^{-3} ,
IPA = 8.22×10^{-4} , and
Network = -1.00×10^{-4}

"Cross" plan marginal probabilities are not shown, but they are of similar magnitude and many have incorrect signs.

¹⁰ This finding is consistent with Banthin's (1992) study of the supplemental insurance choices of Medicare beneficiaries using a national sample of Medicare beneficiaries. By contrast, a market level study by Feldman and others (1993) finds a negative relationship between HMO enrollment and premiums. At the individual level, Gertler and others (1994) find a negative relationship between plan choice probabilities and premiums with a sample of Medicare beneficiaries who participated in an informational intervention that emphasized the financial implications of enrollment in alternative types of supplemental plans.

¹¹ Employer-sponsored markets may provide a better test of the independent effect of premium on plan choice. This is because employer

At the same time, the Twin Cities elderly appear to be more sensitive to cost sharing requirements. In particular, the 61-90 day hospital coinsurance (-0.0075) and the level of the physician visit deductible (-0.0104) have significant negative signs.

The coefficients corresponding to the hospital deductible, the 91 to 150 day hospital coinsurance rate, and coverage of excess physician charges have unexpected signs. Similar to the situation with premiums, there are several data limitations to consider before concluding that the Twin Cities elderly derive greater utility from greater cost sharing. First, the Twin Cities data did not contain large variation in these variables (even among the attributes of medigap plans that varied across individuals; See Table V.7 for descriptive statistics). This is due, in part, to minimum standards for medigap insurance set by the state of Minnesota and the comprehensive nature of HMO plans.¹² Second, those who placed the greatest importance on low cost sharing were enrolled in basic Medicare, the plan with the greatest cost sharing (See Table V.5). The interaction of these two factors helped to push the estimated coefficients in the unexpected direction.¹³

contributions provide a source of variation in the premium facing the enrollee that is unrelated to coverage (See Chapter II, Footnote 2).

¹² The lack of variation in cost sharing is a problem regardless of market area. Experimental approaches for assessing consumer trade-offs, such as conjoint analysis, may prove useful in dealing with the lack of variation in observational data sources.

¹³ Restricting the analysis to choice among the three fee-for-service plans increases the relative amount of variation in the cost sharing attributes. This analysis yields the expected signs on the cost sharing attributes.

and the importance that sample members placed on attributes related to convenience.

One possible explanation may be that the dimensions of convenience that matter to the elderly are not captured by the importance measures. The parameter estimates depend on responses about the importance of waiting time, office hours, and office location. However, these may not be the facets of convenience that matter most to elderly consumers. Instead, the elderly, who are more likely to suffer from physical frailty and have lower time costs, may measure convenience in terms of physical barriers, such as flights of stairs and availability of close parking and public transportation.

Perceived Differences among FFS Plans. The findings suggest that the elderly believe that basic Medicare relegates them to a set of less convenient, lower quality providers. In principle, enrollees in the three FFS plans have access to the same set of providers. However, there is no reason to assume that the elderly in Basic Medicare and the two medigap plans use the same providers. There are large differences in out-of-pocket costs associated with the three plan types, basic Medicare and the two medigap plans. For this reason, elderly decision makers may perceive that enrollment in basic Medicare would force them to seek lower quality (and perhaps less convenient) providers as a way of saving money. An alternative explanation is that enrollees see the same providers but perceive the providers as treating them differently depending on the type of health plan in

which they are enrolled. This could either be the perception of a stigma associated with being enrolled in basic Medicare or the perception that providers behave differently with knowledge of how much their patients must spend out-of-pocket.

Choice Probabilities for "Prototype" Decision Makers. One of the benefits of an approach that assumes that tastes for health plan attributes vary across decision makers is that the results can be used to simulate individualized choice probabilities for particular types of decision makers. Estimated plan choice probabilities are calculated for four prototypical decision makers. Table VI.6 lists the imaginary attribute importance responses for each prototype. Table VI.7 lists the predicted plan choice probabilities associated with each type of decision maker.

Type 1: Emphasis on Value.

This decision maker places the greatest importance on attributes related to financial requirements and coverage. This decision maker wants to get the most services for the lowest expenditure and is willing to trade convenience and some amount of quality. This decision maker has the greatest probability of enrolling in the HMO sector (75.05 percent), the lowest probability of enrolling in a medigap plan (6.15 percent), and the highest probability of remaining in basic Medicare without a supplement (18.80 percent).

Type 2: Emphasis on Quality.

This decision maker places the greatest importance on attributes related to quality and is willing to trade both money and convenience to obtain high quality care. As a result, this decision maker places the greatest importance on attributes related to quality and the least importance on all other types of attributes. The model results suggest that this type of decision maker has the highest overall probability of enrolling in a one of the two medigap plans (85.03 percent) and the lowest overall probability of enrolling in the HMO sector (8.12 percent).

Type 3: Infrequent User.

This decision maker enjoys good health status and uses health care infrequently. Plan enrollment is a way to insure against low probability, high cost events. This decision maker is willing to bear the risk of high out-of-pocket costs in exchange for low premiums. Preventive care is the one service that the decision maker uses on a regular basis. In the event that acute care is required, however, it should be of reasonable quality. In addition, this decision maker views provider choice as an amenity, rather than necessary for quality care, and does not view convenience and quality as trade-offs. Similar to the value prototype, this decision maker is predicted to have a high probability of HMO enrollment (68.75 percent). However, greater concern for convenience decreases the probability of enrollment in basic

Medicare (1.61 percent) and increases enrollment in a traditional medigap plan (29.45 percent).

Type 4: Frequent User.

This decision maker is in poor health status and uses health care services frequently. Unlike the infrequent user (Type 3), service use is a certain event for this decision maker. This decision maker views plan enrollment as a way to prepay for guaranteed access to a particular delivery system. Though more cost conscious than Type 2, this decision maker highly values all plan attributes related to quality. This decision maker is most likely to enroll in one of the two types of medigap plans (80.67 percent). Greater concern for low premiums and cost sharing reduced the probability of medigap enrollment by five percent compared to the prototype decision maker whose greatest concern was plan quality.

Validating Perceptual Parameter Estimates.

Ideally, one would like to assess the validity of the perceptual parameter estimates by comparing them to measures of perceptions obtained through other methods, such as direct questioning with surveys. Unfortunately, the survey of Twin Cities Medicare beneficiaries used in this study did not contain comparable questions about perceived quality of care or perceived convenience. An alternative validation approach is to estimate perceptual parameters for one of the plan attributes that is observable. The value of the perceptual

parameters is then compared to the value of the observed attribute in each plan. Under the assumption that decision makers perceive the observable attribute in the way it is measured in the study, greater consistency between the observed and estimated levels serves as evidence of the validity of the perceptual parameter estimates.

Premiums are chosen for two reasons. First, premiums are measured on a continuous scale, and thus can be represented by continuously measured perceptual parameters. Second, premiums are relatively objective and easy to understand. Unfortunately, none of the studies reviewed in Chapter II contained questions about the degree to which Medicare beneficiaries are well informed about the relative premium levels across plan alternatives.¹⁵

Recall that the size of the perceptual parameter depends on the strength of the relationship between plan choice and the importance that decision makers place on low premiums (other things equal). The bivariate relationship between plan choice and the mean importance of low premiums suggests that the perceptual parameter estimates may not be consistent with actual premiums (See Table VI.8). Table V.3 shows that the group who cares most about low premiums is, in fact, enrolled in the plan with the lowest premiums. However, the group that cares the least about low premiums is enrolled in the IPA plan, not the more expensive medigap plans. Thus,

¹⁵ In a review of the literature on consumers' understanding of health insurance coverage, Marquis and others (1985) suggest that consumers lack knowledge about premiums.

from the bivariate relationships, one would expect all of the perceptual parameter estimates to be positive relative to basic Medicare which is set to zero. At the same time, parameters representing perceived IPA premiums should be the largest and those representing the Network HMO should be the smallest relative to basic Medicare. (Table VI.8 shows the expected ranking of the premium estimates).

As expected, the bivariate relationships between plan choice and premium importance are revealed in parameter estimates from a model that contains only constants and perceptual parameter estimates representing premiums (See Table VI.8). However, when the observed attributes and unobserved quality of care are added to the model, the premium parameters become small and insignificantly different from zero. Thus, the perceptual parameter estimates in the full model suggest that the elderly are choosing as if they perceived HMO premiums to be higher than medigap premiums, when this is not in fact the case.

Maintaining the assumption that decision makers' true perceptions were consistent with actual premiums, there are several alternative explanations for the failure of the estimates to approximate actual premiums. First, low premium importance may not be a valid measure of decision makers' true preferences for low premiums, other things equal. Second, there may not be enough covariation (either in the sample or in the population) among the attribute importance responses to separately estimate the independent effect on

utility of perceived premiums. For example, the importance of low premiums and the importance of low cost sharing are strongly correlated in the sample. Third, decision makers' choice processes may not be well approximated by utility maximization theory and/or the multiattribute utility function.

Effect of Omitting Latent Attributes.

If decision makers perceive relationships between the latent attributes and the observable attributes, then omitting the latent attributes should influence inferences about observable attributes. Evidence of omitted variable bias is obtained by comparing two different model specifications. Model 4 includes observable and latent attributes. Model 5 includes only observable attributes. Table VI.9 reports the preference and variance parameter estimates corresponding to observable attributes for each of the two models.

Model 5: No latent attributes, non-zero measurement error.

$$V_{i,j} = x_{j,2}(\alpha_1 s_{i,1} + \gamma_1 \epsilon_{i,1}) + x_{j,2}(\alpha_2 s_{i,2} + \gamma_2 \epsilon_{i,2}) + \dots + x_{j,13}(\alpha_{13} s_{i,13} + \gamma_{13} \epsilon_{i,13})$$

where $j = 1, \dots, J$.

A likelihood ratio test was used to test the hypothesis that Model 4 and Model 5 are equivalent.

This hypothesis was strongly rejected (Chi-square = 173.64, degrees of freedom = 8). This rejection suggests that the latent attributes are important for explaining the choice behavior observed in the data. Further, a comparison of these two models suggests that omitting the latent attributes from the model specification leads to omitted variable bias. Table VI.10 helps to illustrate the extent of this bias. This table shows the magnitude of the effect on predicted choice probabilities for selected attributes.

The inclusion of the latent attributes eliminates the perverse finding that higher premiums are associated with higher utility. Controlling for the latent attributes decreases the preference parameter corresponding to premiums from 0.0033 to 0.0004 (not significant). The reduction in the size of the coefficient on premium resulting from the addition of the latent attributes suggests that the Twin Cities elderly perceived a positive relationship between the value of the latent attributes and premiums.

Preventive care and a reduced paperwork burden are attributes that are associated with HMO plans. Adding the latent attributes to the model increases the magnitude of the preference parameters corresponding to the requirement that the enrollees submit claims from -0.0249 (not significant) to -0.1610. At the same time, the preference parameter corresponding to the

coverage of preventive care more than doubles from 0.1965 to 0.4135. These changes are consistent with (1) a perceived negative relationship between the latent attributes and the coverage of preventive care and (2) a perceived positive relationship between the latent attributes and the submission of claims requirement. This finding suggests that omitting the latent attributes may lead analysts to understate the value to the elderly of services traditionally offered by HMOs.

Adding the latent attributes decreases the preference equation parameter corresponding to drug coverage from 0.3146 to 0.18856. Adding the latent attributes to the model also reduces the preference parameters corresponding to eyeglass coverage from 0.1460 to 0.0524 (not significant). These reductions are consistent with a perceived positive relationship between the latent attributes and drug and eyeglasses coverage. Finally, adding the latent attributes to the model substantially increases the preference parameters corresponding to choice of physician from 0.0535 (not significant) to 0.2527. This change is consistent with a perceived negative relationship between the latent attributes and physician choice.

Subgroup Analysis.

Recall that the purpose of the attribute importance measures is to control for differences in preference across decision makers. Demographic characteristics such as age,

health status and income often are used as proxies for preferences in studies of health plan choice. The choice model used in this study does not include these variables. Instead, the important measures are intended to be more direct measures of preferences. In order to be a valid measure, however, the importance measures should capture differences across individuals that are consistent with theory or common sense. For example, people in poor health status would be expected to have a different pattern of attribute importance responses compared to healthier people. Healthier people would be expected to place less importance on drug coverage and provider choice. (Table V.5 compares the importance of health plan attributes across subgroups.) A subgroup analysis was performed in order to determine whether variation in the importance responses was sufficient to capture differences in preferences across subgroups.

The sample was split into subgroups on the basis of policy relevant characteristics. These characteristics include health status, age, and income level. Choice models were estimated separately for subgroups for each characteristic (See Table VI.11 and Table VI.12). Because of limited sample size, the model specification used in the subgroup analysis assumed no measurement error in the importance measures. No difference in the parameter estimates across the subgroups would suggest that the attribute importance measures are capturing individual variation in preferences. Alternatively, differences across

subgroups would suggest the need for understanding the reasons why the attribute importance question was failing to capture expected patterns of preferences.¹⁶

A likelihood ratio test was used to compare the parameter estimates resulting from the split sample analysis to the results from the pooled sample (equivalent to Model 3). In the case of health status and income, a likelihood ratio test rejected the hypotheses that the parameters from the split samples were equivalent to the estimates resulting from the pooled sample.¹⁷ The results of these tests suggest that there were differences in tastes across these two subgroups of individuals that were not fully captured by their attribute importance responses. However, it is difficult to interpret these differences substantively. While differences in point estimates of model parameters across subgroups appear large, these differences are not significant when their confidence intervals are considered.

Nonetheless, one interesting pattern does arise in examining differences across subgroups in perceptual parameters representing perceived quality (See Table VI.12). For each of the four characteristics considered, the relative ranking of the perceptual parameters within each subgroup is

¹⁶ There are a number of explanations, including the lack of incentive or motivation to answer truthfully, misunderstanding of the question, and the small number of response categories.

¹⁷ Degrees of freedom = 19 for test and with a 0.05 chi-square critical value of 30.14:

Health problems vs. No health problems: Chi-square = 51.05,
Old vs. Young: Chi-square = 12.75, and
Low income vs. Upper income: Chi-square = 94.38.

the same as in the pooled Model 3 (See Table VI.3 and Table VI.4). Within each subgroup, the HMO plans are perceived as having lower quality than the Medigap plans. As in the pooled Model 3, the pattern was less clear for convenience. Again, variation across subgroups in the perceptual parameters representing convenience may be due to the lack of a strong relationship in the sample between plan choices and the importance of attributes related to convenience.

Policy Experiment.

The parameter estimates in the final model specification (Model 4) can be used to simulate the effect of an intervention that influences decision makers' perceptions of the relative amount of quality in each of the five health plans. The predicted effect of such an intervention is measured by comparing the average predicted choice probabilities resulting from the simulated experiment to those resulting from the baseline Model 4.

One can imagine two types of interventions that could result in changes in perceptions. In the first intervention, perceptions change as the result of information about quality. Unfortunately, there are no studies that document objective or technical quality of care from the same time period for the same Twin Cities population. Nonetheless, results from research during the period discussed in Chapter II suggests there are not large differences in a number of process and outcome measures of quality across sectors. An

intervention that communicated information about this lack of objective differences in quality across the two sectors could result in a reduction in perceived quality differences. In the second intervention, perceptions change as the result of changes in the organization, delivery, or outcomes of care across plans. Here, information about these changes is conveyed through normal channels, such as communication among friends and family.

Two types of experiments that succeed in reducing perceived differences in quality between fee-for-service sector and HMOs are simulated. Each has a different assumption about the effect of the intervention on perceived differences between basic Medicare and the four supplemental plans. **Experiment 1** eliminates perceived differences in quality across the four supplemental plans (the two medigap plans and the two HMOs), while leaving unchanged the decision makers' perception that the quality of care in supplemental plans is greater than that offered by the basic Medicare entitlement. The idea is that decision makers continue to perceive a positive increment in quality from enrolling in a supplemental plan. This outcome can be represented in the model by setting the perceptual parameter corresponding to perceived quality to 0.2133, the average level in the four supplemental plans. **Experiment 2** eliminates perceived differences in quality across all five plan types. This outcome can be represented in the model by setting the

perceptual parameter corresponding to perceived quality to zero in all four supplemental plans.

Total Sample. Assumptions about the impact of the intervention on perceived differences in quality between basic Medicare and the four supplemental plans turn out to make large substantive differences in its predicted effect. Table VI.13 shows the results of both imaginary interventions. The results of **Experiment 1** suggest an increase in overall enrollment in HMO plans from 70.84 percent to 82.40 percent. In addition to increasing enrollment, the intervention also influenced the predicted distribution of enrollees within the two types of HMOs. The baseline model predicts that 63.14 percent of HMO enrollees will enroll in the Network option. After the intervention, the percent of HMO enrollees in the Network options falls to 38.79 percent. By contrast, the results of **Experiment 2** suggest an overall decrease in enrollment in HMO plans from 70.84 to 68.51 percent. There is also a similar reduction in the predicted proportion of HMO enrollees choosing the Network plan from the baseline. At the same time, the average probability of enrollment in basic Medicare more than doubles from 9.63 to 21.77 percent.

Prototype Decision Makers. Even though the intervention is assumed to influence all decision makers' perceptions of plan quality in the same way, its impact on choice probabilities depends on the decision makers' tastes for health plan attributes. This differential effect is

illustrated by calculating the predicted choice probabilities for each of the four prototype decision makers discussed above under each of the two experiments. Table VI.14 lists the results.

The intervention has the least effect on the value conscious (Type I and Type III) decision makers who place the least importance on attributes related to quality.

Experiment 1 increases the probability that Type I and Type III decision makers enroll in an HMO by about 8 to 10 percent. **Experiment 2** decreases the probability that the Type I decision maker enrolls in an HMO by 18 percent and increases the probability of enrollment in Basic Medicare by 21 percent. At the same time, **Experiment 2** increases the probability that the Type III decision maker enrolls in an HMO by less than two percent.

By contrast, the intervention had the greatest impact on the decision makers (Type II and Type IV) who place the greatest importance on quality. For both types, **Experiment 1** and **Experiment 2** increased the probability of enrollment in an HMO by as much as 16 to 33 percent. The intervention has much less influence on the prototypical decision makers who value low premiums and low cost sharing relatively more than attributes related to quality. Among this group, the intervention increases the probability of enrolling in the HMO sector by 11 percent at most. However, in neither experiment was the intervention sufficiently strong to

increase the probability of enrollment in HMOs to greater than 50 percent.

If decision makers who value quality highly are also in poorer health status, then the intervention could result in adverse selection. The fear of adverse selection may reduce the incentive for HMOs (in the absence of risk adjustment mechanisms) to participate in good faith in public sector efforts to collect and disseminate information about quality. It is interesting to note that the subsample judged to be in poor health status placed greater importance on financial and coverage attributes and less importance on attributes related to quality of care than those in good health. This relationship suggests that this type of intervention would not necessarily result in adverse selection, if applied to the population of Twin Cities elderly represented by this sample.

Summary

This chapter began with a discussion of a number of restrictions placed on the fully identified model presented in Chapter V. The final model contains two latent attributes representing decision makers' perceptions of quality of care and convenience. Overall, the findings suggest that the elderly perceived the quality of care in HMOs as lower than in the medigap plans but higher than in basic Medicare. The results also suggest that simply ignoring relevant unobserved attributes leads to omitted variable bias.

The results can be used to simulate the effect of a policy experiment on plan choice. Two types of interventions that reduced differences in perceived quality across plans were simulated. Both interventions led to changes in enrollment probabilities within the HMO sector. Their effect on overall enrollment in the HMO sector depends on the effect of the intervention on perceived quality within the FFS sector. The results also show that the intervention had a stronger impact on the choice probabilities of those who highly value attributes related to quality of care.

Figure VI.1: Utility Contribution of Latent Attributes Relative to Medicare Evaluated at Mean Levels of Attribute Salience

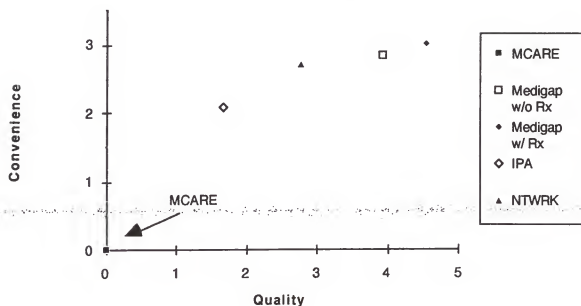


Table VI.1: Preference Equation Parameter Estimates from
Alternative Health Plan Choice Model Specifications Assuming No
Measurement Error

Attribute importance indicators	Observed attribute	Model 1: Observed attributes Only	Model 2: Observed attributes + 7 latent attributes	Model 3: Observed attributes + 2 latent attributes
Premium	Monthly premium	0.0038** (0.0006)	0.0019* (0.0007)	0.0020** (0.0007)
Out-of-pocket costs	Hospital deductible	0.0014** (0.0002)	0.0013** (0.0002)	0.0013** (0.0002)
	Hospital 61-90 day coinsurance	-0.0120** (0.0016)	-0.0058** (0.0017)	-0.0053** (0.0016)
	Hospital 91-150 day coinsurance	0.0034** (0.0005)	0.0014 (0.0009)	0.0012 (0.0009)
	Physician deductible	-0.0059** (0.0843)	-0.0065** (0.0006)	-0.0064** (0.0006)
	Covers excess MD charges (1,0)	-0.4362** (0.0763)	-0.4245** (0.0856)	-0.4071** (0.0843)
	Covers SNF beyond MCARE (1,0)	0.4435** (0.0465)	0.3946** (0.0718)	0.3877** (0.0701)
Drug coverage	Covers outpatient Rx (1,0)	0.2915** (0.0272)	0.1468** (0.0326)	0.1454** (0.0318)
Eyeglass coverage	Covers eyeglasses (1,0)	0.1006** (0.0301)	0.0398 (0.0338)	0.0371 (0.0329)
Preventive care coverage	Covers preventive care (1,0)	0.1798** (0.0343)	0.2489** (0.0416)	0.2482** (0.0409)
Choice of hospital	Permits choice of hospital (1,0)	0.1556** (0.0336)	0.2196** (0.0373)	0.2116** (0.0363)
Choice of MD	Permits choice of MD (1,0)	0.0652* (0.0307)	0.1956** (0.0402)	0.2011** (0.0394)
Paperwork burden	Submit claims for reimbursement (1,0)	0.0146 (0.0308)	-0.0806* (0.0410)	-0.0842* (0.0401)
Likelihood value		-1631.9311	-1547.6115	-1556.1340

*Significantly different from zero at 0.05 level.
**Significantly different from zero at 0.01 level.

Table VI.2: Perceptual Parameter Estimates (MLE) from
Alternative Health Plan Choice Model Specifications Assuming
No Measurement Error

	Latent attribute	Basic Medicare	Medigap w/o Rx	Medigap w/ Rx	IPA	Network
Model 2 Observed attributes + 7 latent attributes	Overall quality	Restricted to 0.0000	-0.0044 (0.1346)	0.0917 (0.1043)	0.0151 (0.0785)	0.0395 (0.0745)
	Not being rushed from hospital	" "	0.1070 (0.1062)	0.2007* (0.0923)	0.0143 (0.0660)	0.0467 (0.0636)
	Referral to Specialists	" "	0.2243* (0.1234)	0.0869 (0.1030)	0.0574 (0.0767)	0.1772* (0.0734)
	Office location	" "	0.0533 (0.1143)	0.2032 (0.1097)	-0.0322 (0.0730)	0.1208 (0.0670)
	Office hours	" "	-0.0087 (0.1270)	-0.0404 (0.1065)	0.0702 (0.0723)	0.0552 (0.0687)
	Office waiting time	" "	0.1265 (0.1347)	0.3404 (0.1130)	0.0581 (0.0851)	0.1397 (0.0817)
	Appointment waiting time	" "	0.3678 (0.1402)	-0.0196 (0.1099)	-0.0343 (0.0840)	-0.0683 (0.0808)
Model 3 Observed attributes + 2 latent attributes	Overall quality	Restricted to 0.000	0.1070** (0.0391)	0.1290** (0.0324)	0.0212 (0.0267)	0.1861** (0.0269)
	Overall conven- ience	" "	0.0513 (0.0353)	0.0663* (0.0307)	0.0180 (0.0231)	0.0633** (0.0231)

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.3: Preference Equation Parameter Estimates from Alternative Health Plan Choice Model Specifications with and without Measurement Error

		Model 3: Observed attributes + 2 latent attributes; no measurement error		Model 4: Observed attributes + 2 latent attributes; non-zero measurement error	
Attribute importance indicators	Observed attribute	Preference $\hat{\alpha}_k$	Variance $\hat{\gamma}_k$	Preference $\hat{\alpha}_k$	Variance $\hat{\gamma}_k$
Premium	Monthly premium	0.0020** (0.0007)	Restricted to 0.000	0.0004 (0.0013)	0.0432** (0.0084)
Out-of- pocket costs	Hospital deductible	0.0013** (0.0002)	" "	0.0023** (0.0006)	0.0052** (0.0018)
	Hospital 61-90 day coinsurance	-0.0053** (0.0016)		-0.0075** (0.0022)	
	Hospital 91- 150 day coinsurance	0.0012 (0.0009)		0.0013 (0.0014)	
	Physician deductible	-0.0064** (0.0006)		-0.0104** (0.0012)	
	Covers excess MD charges (1,0)	-0.4071** (0.0843)	" "	-0.7360** (0.1563)	0.0368 (0.9983)
	Covers SNF beyond MCARE (1,0)	0.3877** (0.0701)		0.6484** (0.1290)	
	Covers outpatient Rx (1,0)	0.1454** (0.0318)		0.1856** (0.0416)	
	Eyeglass coverage	0.0371 (0.0329)		0.0524 (0.0392)	
	Preventive care coverage	0.2482** (0.0409)		0.4135** (0.0916)	
	Choice of hospital	0.2116** (0.0363)		0.2381** (0.0522)	
	Choice of MD	0.2011** (0.0394)		0.2527** (0.0566)	
	Paperwork burden	Submit claims for reimburse- ment (1,0)		-0.0842* (0.0401)	
Likelihood value		-1558.0519		-1541.9993	

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.4: Perceptual Parameter Estimates (MLE) from Alternative Health Plan Choice Model Specifications with and without Measurement Error

	Latent attribute	Basic Medicare	Medigap w/o Rx	Medigap w/ Rx	IPA	Network
Model 3 Observed attributes + 2 latent attributes; zero measurement error	Overall Quality	Restricted to 0.000	0.1070** (0.0391)	0.1290** (0.0324)	0.0212 (0.0267)	0.0861** (0.0269)
	Overall convenience	" "	0.0513 (0.0353)	0.0663* (0.0307)	0.0180 (0.0231)	0.0633** (0.0231)
Model 4 Observed attributes + 2 latent attributes; non-zero measurement error	Overall quality	" "	0.2601** (0.0921)	0.3001** (0.0919)	0.1097 (0.0702)	0.1833** (0.0710)
	Overall convenience	" "	0.1732* (0.0790)	0.1842* (0.0802)	0.1270 (0.0658)	0.1661** (0.0653)

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.5: Change in the Average Predicted Probability of Plan Choice from Adding or Removing Covered Services and Paperwork Burden to or from Health Plan

Health Plan Type	Service	Model 3 No Measurement Error + 2 Latent Attributes	Model 4 Measurement Error + 2 Latent Attributes
	SNF beyond MCARE		
Basic Medicare	Add	0.2584	0.1804
Medigap without drugs	Remove	-0.0440	-0.0430
Medigap with drugs	Add	0.1152	0.1343
IPA	Add	0.3658	0.4705
Network	Add	0.3010	0.3489
	Preventive Care		
Basic Medicare	Add	0.0092	0.0101
Medigap without Rx	Add	0.1644	0.2553
Medigap with Rx	Add	0.1434	0.2385
IPA	Remove	-0.1313	-0.1691
Network	Remove	-0.1974	-0.2533
	Submit Claims		
Basic Medicare	Remove	0.0024	0.0026
Medigap without Rx	Remove	0.0498	0.1401
Medigap with Rx	Remove	0.0445	0.1394
IPA	Add	-0.0582	-0.0966
Network	Add	-0.0760	-0.1325

Table VI.6: Attribute Importance Responses for Prototype Decision Makers

Plan Attributes Contained in Twin Cites Survey	Type 1: Value	Type 2: Quality	Type 3: Good Health; Low Use	Type 4: Poor Health; High Use
Low premiums	7	1	7	4
Low cost sharing	7	1	1	4
Prescription drug coverage	7	1	1	7
Eyeglass coverage	1	1	1	1
Preventive care coverage	7	1	7	1
Choice of physician	1	7	1	7
Choice of hospital	1	7	1	7
Overall Quality of Care	4	7	4	7
Referrals to specialists	4	7	4	7
Not being rushed from hospital	4	7	4	7
Paperwork burden	1	1	4	1
Clinic/office location	1	1	4	4
Clinic/office hours	1	1	4	4
Clinic/office wait	1	1	4	4
Waiting time for appointment	1	1	4	4

Note: 1 = the attribute 'does not matter' to the respondent,
 4 = the respondent would 'like to have' the attribute, and
 7 = the respondent 'has to have' the attribute.

Table VI.7: Predicted Choice Probabilities for Prototype
Decision Makers

	Basic Medicare	Medigap w/o Rx	Medigap w/ Rx	IPA	Network
Type 1: Value	18.80	4.74	1.41	10.75	64.30
Type 2: Quality	6.90	31.61	53.38	5.62	2.50
Type 3: Good Health; Low Use	1.61	7.35	22.10	14.10	54.65
Type 4: Poor Health; High Use	6.44	39.69	40.98	4.47	8.42

Table VI.8: Observed Values, Perceptual Parameter Estimates, and Expected Rankings for Plan Premiums^{a,b}

Health Plan	Observed Monthly Premium ^c	Expected Ranking ^d	Constants Only	Full Model
Basic Medicare	\$28.00	1	0.0000	0.0000
Medigap without drugs	77.00 (11.25)	3	0.3018 (0.0709)	0.0300 (0.1030)
Medigap with drugs	104.00 (13.90)	4	0.3362 (0.0694)	-0.0563 (0.0926)
IPA	53.00	5	0.3723 (0.0556)	0.3382** (0.0768)
Network	43.00	2	0.1965 (0.0518)	0.1742* (0.0708)

^a Estimates are obtained under the assumption that higher premiums are associated with lower utility. The restriction that $\alpha_{\text{premium}}^* = -1.00$ is imposed.

^b The perceptual parameter representing premiums is restricted to zero in the Basic Medicare plan.

^c Mean and standard deviation are reported for the two Medigap plans. Premiums do not vary within individual for the Basic Medicare, IPA or Network plans.

^d Expected ranking from examining the bivariate relationship between enrollment and the importance of low premiums (See Table V.3).

* Statistically significant at the 0.05 level.

** Statistically significant at the 0.01 level.

Table VI.9: Preference Equation Parameter Estimates from Alternative Health Plan Choice Model Specifications with and without Unobserved Attributes

		Model 4: Observed attributes + 2 latent attributes; non-zero measurement error		Model 5: Observed attributes only; non-zero measurement error	
Attribute importance indicators	Observed attribute	Preference $\hat{\alpha}_k$	Variance $\hat{\gamma}_k$	Preference $\hat{\alpha}_k$	Variance $\hat{\gamma}_k$
Premium	Monthly premium	0.0004 (0.0013)	0.0432** (0.0084)	0.0033** (0.0010)	0.0301** (0.0066)
Out-of- pocket costs	Hospital deductible	0.0023** (0.0006)	0.0052** (0.0018)	0.0019** (0.0003)	0.0001 (0.0061)
	Hospital 61-90 day coinsurance	-0.0075** (0.0022)		-0.0080** (0.0022)	
	Hospital 91-150 day coinsurance	0.0013 (0.0014)		0.0003 (0.0010)	
	Physician deductible	-0.0104** (0.0012)		-0.0079** (0.0009)	
	Covers excess MD charges (1,0)	-0.7360** (0.1563)	0.0368 (0.9983)	-0.6476** (0.1141)	0.4281 (0.3852)
	Covers SNF beyond MCARE (1,0)	0.6484** (0.1290)		0.5693** (0.0839)	
	Drug coverage	Covers outpatient Rx (1,0)		0.3146** (0.0651)	
Eyeglass coverage	Covers eyeglasses (1,0)	0.0524 (0.0392)		0.1046* (0.0420)	
Preventive care coverage	Covers preventive care (1,0)	0.4135** (0.0916)		0.1965** (0.0521)	
Choice of hospital	Permits choice of hospital (1,0)	0.2381** (0.0522)		0.1968** (0.0624)	
Choice of MD	Permits choice of MD (1,0)	0.2527** (0.0566)		0.0535 (0.0411)	
Paperwork burden	Submit claims for reimburse- ment (1,0)	-0.1610* (0.0771)		-0.0249 (0.0382)	
Likelihood value		-1541.9993		-1628.8211	

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.10: The Effect of Excluding Latent Attributes on Predicted Changes in Average Plan Choice Probabilities from Adding or Removing Selected Attributes

Attribute	Health Plan Type	Attribute Change	Model 5: Observed attributes only ^a	Model 4: Observed and latent attributes ^b
Drug Coverage	Basic Medicare	Add	17.27	3.34
	Medigap w/o Rx	Add	8.50	3.56
	Medigap w/ Rx	Remove	-3.78	-2.29
	IPA	Add	25.02	13.39
	Network	Remove	-22.98	-12.98
Choice of MD	Basic Medicare	Remove	-2.46	3.49
	Medigap w/o Rx	Remove	-1.04	-3.63
	Medigap w/ Rx	Remove	-1.05	-3.65
	IPA	Remove	-4.62	-14.97
	Network	Add	4.84	18.98
Preventive care	Basic Medicare	Add	10.59	1.01
	Medigap w/o Rx	Add	4.68	25.53
	Medigap w/ Rx	Add	4.01	23.85
	IPA	Remove	-12.46	-16.85
	Network	Remove	-15.41	-25.33
Submit claims	Basic Medicare	Remove	1.00	-0.26
	Medigap w/o Rx	Remove	0.48	14.01
	Medigap w/ Rx	Remove	0.30	13.94
	IPA	Add	-2.26	-9.66
	Network	Add	-2.42	-13.25

^a This column can be added to the predicted choice probabilities in Table VI.5 for Model 5 to obtain the overall predicted choice probability obtained after adding or removing attribute.

^b This column can be added to the predicted choice probabilities in Table VI.5 for Model 4 to obtain the overall predicted choice probability obtained after adding or removing attribute.

Table VI.11: Preference Equation Parameter Estimates by Subgroup Assuming No Measurement Error and including Two Latent Attributes

Attribute importance indicators	Observed attribute	Model 6: Health problems n = 438	Model 7: No health problems n = 836	Model 8: Age 75 and over n = 568	Model 9: Age 74 and under n = 706
Premium	Monthly premium	0.0030* (0.0012)	0.0013 (0.0009)	0.0006 (0.0009)	0.0041** (0.0013)
Out-of-pocket costs	Hospital deductible	0.0009** (0.0003)	0.0081 (0.0114)	0.0003 (0.0007)	0.0017** (0.0004)
	Hospital 61-90 day coinsurance	0.0047 (0.0028)	-0.5010 (0.8278)	-0.0074** (0.0024)	-0.0008 (0.0033)
	Hospital 91-150 day coinsurance	-0.0027 (0.0014)	0.2395 (0.4308)	0.0041* (0.0017)	-0.0016 (0.0018)
	Physician deductible	-0.0053** (0.0010)	-0.0059** (0.0008)	-0.0056** (0.0009)	-0.0076** (0.0009)
	Covers excess MD charges (1,0)	-0.2564 (0.1652)	-0.3306** (0.1205)	-0.4051** (0.1395)	-0.4162** (0.1321)
	Covers SNF beyond MCARE (1,0)	0.3024* (0.1269)	0.3828 (0.0991)	0.3667** (0.1116)	0.4895** (0.1032)
Drug coverage	Covers outpatient Rx (1,0)	0.1227* (0.0560)	0.1607 (0.0400)	0.1194** (0.0453)	0.1711** (0.0461)
Eyeglass coverage	Covers eyeglasses (1,0)	0.0700 (0.0537)	0.0228 (0.0425)	0.0860 (0.0469)	-0.0079 (0.0475)
Preventive care coverage	Covers preventive care (1,0)	0.1056 (0.0632)	0.3418** (0.0559)	0.1897** (0.0560)	0.2947** (0.0633)
Choice of hospital	Permits choice of hospital (1,0)	0.2426** (0.0627)	0.1890** (0.0465)	0.1547** (0.0514)	0.2515** (0.0531)
Choice of MD	Permits choice of MD (1,0)	0.0231 (0.0675)	0.2901** (0.0497)	0.1552** (0.0564)	0.2455** (0.0560)
Paperwork burden	Submit claims for reimbursement (1,0)	-0.1091 (0.0652)	-0.1115* (0.0550)	-0.0500 (0.0527)	-0.1316* (0.0654)
Likelihood value		-556.7091	-959.7655	-758.2035	-777.4214

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.11 (cont'd): Preference Equation Parameter Estimates by Subgroup Assuming No Measurement Error and including Two Latent Attributes

Attribute importance indicators	Observed attribute	Model 10: Upper income n = 719	Model 11: Lower income n = 555
Premium	Monthly premium	0.0040** (0.0011)	0.0007 (0.0010)
Out-of-pocket costs	Hospital deductible	0.0442 (0.0852)	0.0012** (0.0003)
	Hospital 61-90 day coinsurance	-0.8667 (1.7000)	0.0035 (0.0028)
	Hospital 91-150 day coinsurance	0.3461 (0.6796)	-0.0032** (0.0014)
	Physician deductible	-0.0053** (0.0008)	-0.0057** (0.0008)
	Covers excess MD charges (1,0)	-0.0722 (0.1304)	-0.3918** (0.1252)
	Covers SNF beyond MCARE (1,0)	0.4642** (0.1178)	0.2833** (0.1008)
Drug coverage	Covers outpatient Rx (1,0)	0.1638** (0.0454)	0.1214** (0.0457)
Eyeglass coverage	Covers eyeglasses (1,0)	0.0923* (0.0476)	-0.0130 (0.0470)
Preventive care coverage	Covers preventive care (1,0)	0.3588** (0.0627)	0.1666** (0.0577)
Choice of hospital	Permits choice of hospital (1,0)	0.2238** (0.0479)	0.1855** (0.0577)
Choice of MD	Permits choice of MD (1,0)	0.2174** (0.0519)	0.1773** (0.0616)
Paperwork burden	Submit claims for reimbursement (1,0)	-0.1512* (0.0743)	-0.0789** (0.0517)
Likelihood value		-784.5243	-710.2954

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.12: Perceptual Parameter Estimates (MLE) by Subgroup
Assuming no Measurement Error

	Latent attribut e	Basic Medicare	Medigap w/o Rx	Medigap w/ Rx	IPA	Network
Model 6 Health problems	Overall Quality	Restricted to 0.0000	0.1122 (0.0692)	0.1309* (0.0481)	0.0086 (0.0374)	0.0601 (0.0499)
	Overall convenienc e	" "	0.0147 (0.0619)	0.0275 (0.0462)	0.0303 (0.0306)	0.0499 (0.0319)
Model 7 No health problems	Overall quality	Restricted to 0.0000	0.0959 (0.0527)	0.1138* (0.0483)	-0.0002 (0.0388)	0.0691 (0.0379)
	Overall convenienc e	" "	0.1138 (0.04893)	0.0659 (0.0461)	0.0030 (0.0347)	0.0589 (0.0343)
Model 8 Age 75+	Overall Quality	Restricted to 0.0000	0.0533 (0.0575)	0.0895* (0.0411)	0.0136 (0.0341)	0.0466 (0.0359)
	Overall convenienc e	" "	0.0712 (0.0510)	0.1044** (0.0383)	0.0495 (0.0304)	0.0851* (0.0327)
Model 9 Age 74 and under	Overall quality	Restricted to 0.0000	0.1334* (0.0606)	0.1817** (0.0580)	0.0166 (0.0441)	0.1114** (0.0429)
	Overall convenienc e	" "	0.0394 (0.0551)	0.0106 (0.0562)	-0.0082 (0.0372)	0.0447 (0.0354)
Model 10 Upper income	Overall Quality	Restricted to 0.0000	0.0690 (0.0600)	0.9012 (0.0535)	-0.0205 (0.0464)	0.0198 (0.0479)
	Overall convenienc e	" "	0.0272 (0.0560)	0.0309 (0.0506)	-0.0276 (0.0408)	0.0272 (0.0408)
Model 11 Lower income	Overall quality	Restricted to 0.0000	0.0963 (0.0612)	0.1306** (0.0473)	-0.0396 (0.0354)	0.0752* (0.0342)
	Overall convenienc e	" "	0.0493 (0.0538)	0.0508 (0.0423)	0.0537 (0.0298)	0.0718* (0.0298)

*Significantly different from zero at 0.05 level.

**Significantly different from zero at 0.01 level.

Table VI.13: Average Predicted Choice Probabilities Under Different Assumptions about Decision Makers' Perceptions of Health Plan Quality

	Basic Medicare	Medigap w/o Rx	Medigap w/ Rx	IPA	Network
Baseline (Model 5)	9.63	8.11	11.44	26.11	44.73
Experiment 1	7.04	7.28	6.31	50.43	31.96
Experiment 2	21.77	3.79	5.95	41.93	26.58

Table VI.14: Predicted Choice Probabilities Under Different Assumptions about Decision Makers' Perceptions' of Health Plan Quality

		Basic Medicare	Medigap w/o Rx	Medigap w/ Rx	IPA	Network
Type 1: Value	Baseline (Model 5)	18.80	4.74	1.41	10.75	64.30
	Experiment 1	14.35	1.54	3.74	19.22	64.52
	Experiment 2	40.28	9.98	1.84	15.35	43.19
Type 2: Quality	Baseline (Model 5)	6.90	31.61	53.68	5.62	2.50
	Experiment 1	6.51	20.00	31.75	38.83	2.89
	Experiment 2	39.23	13.93	18.51	26.37	1.46
Type 3: Good Health; Low Use	Baseline (Model 5)	1.61	7.35	22.10	14.10	54.85
	Experiment 1	1.64	5.17	13.94	30.83	48.41
	Experiment 2	18.67	3.50	7.36	39.03	31.43
Type 4: Poor Health; High Use	Baseline (Model 5)	6.44	39.69	40.98	4.47	8.42
	Experiment 1	6.18	25.17	23.35	34.09	11.22
	Experiment 2	56.98	1.05	8.03	21.45	3.07

Chapter VII: Conclusion

This study specified a multiattribute health plan choice model that controlled for the effect of theoretically relevant but unobserved attributes. The study treated Twin Cities Medicare beneficiaries' perceptions of quality of care and convenience as model parameters to be estimated. The fact that a measure of attribute importance was contained in the Twin Cities Medicare survey made it possible to estimate perceptual parameters without relying on costly panel data.

Consistent with popular concern about the quality of care in HMOs, the findings suggest that the Twin Cities elderly perceived quality of care in HMOs as lower than that in the two medigap plans, but higher than that in the basic Medicare plan. This finding provides policy makers with insight into the unwillingness of some Twin Cities Medicare beneficiaries to enroll in HMOs despite substantially lower premiums and cost sharing requirements. The findings suggest that further reductions in the relative price of HMOs would do little to increase enrollment. By contrast, estimated choice model parameters are used to predict that eliminating perceived differences in quality between HMOs and medigap plans could substantially increased enrollment in the HMO sector.

The findings also suggest that the failure to control for unobserved attributes leads to biased inferences about the effect of observable attributes on plan choice.

Specifically, when unobserved attributes are omitted, coefficient estimates suggest that decision makers associate higher premiums with higher utility. Also, omitting latent attributes may lead researchers to understate the importance of two plan attributes associated with HMOs: preventive care and the elimination of paperwork burden.

The following two sections discuss a number of potential applications of the approach to perceptual parameter estimation developed in this study, advantages of perceptual parameter estimates over consumer satisfaction measures, and several methodological issues for consideration in future applications.

Future Applications.

In addition to helping policy makers understand how perceived quality influences plan choice, the parameter estimates can be used to gauge the degree of consistency between consumers' perceptions and objective measures of quality of care. Large inconsistencies may warrant informational interventions. It would have been interesting to compare the perceptual parameter estimates resulting from the Twin Cities survey data to objective measures of quality of care across the two sectors for the Twin Cities Medicare population in the mid-1980s. Unfortunately, there is no single study, or collection of studies, documenting differences in objective quality of care for this population during this time period.

Moreover, policy researchers can use the approach to perceptual parameter estimation in the development and evaluation of policy interventions aimed at altering plan choice behavior. Researchers can use this approach to predict the effect of interventions that change readily observable characteristics of plans, such as premiums or cost sharing requirements, controlling for the effect of otherwise unobserved attributes such as quality of care. Researchers can also use this approach to better understand perceptions of quality and how these perceptions are changed by information.

Specifically, the perceptual and preference equation parameters could be used to measure a treatment effect resulting from informational interventions in experimental or quasi-experimental research designs. In theory, information helps decision makers to choose plans that best meet their preferences. Thus, information is expected to increase the consistency between actual plan attributes (observed or unobserved by the researcher) and the importance that decision maker place on these attributes. In other words, information should help consumers to choose health plans that offer the attributes that are important to them. Model parameters can be used measure the impact of information on this relationship.

Finally, this approach may also provide insight into consumer definitions of quality. Survey and focus group research suggests that assessments of the interpersonal

skills of providers dominate consumer evaluations of quality (Agency for Health Care Policy and Research, 1994, Walker, 1990; Ware et al., 1983). At the same time, consumers express little interest in information about technical quality (Agency for Health Care Policy and Research, 1994). However, these attitudes do not necessarily imply that consumers are indifferent to technical aspects of care. Instead, consumers may use interpersonal qualities of providers as signals of underlying technical quality. If this were the case, then consumers might assign less weight to interpersonal skills in making plan and provider choices when provided with easy to understand technical quality information. Perceptual parameter estimates may help in distinguishing between these two explanations. Researchers could first solicit attribute importance responses for both technical and interpersonal aspects of care. Researchers could then use statistical techniques to determine whether a model that treats quality as one combined attribute can be used as a restriction on a model that treats technical quality and interpersonal quality as separate attributes.

Advantages over Consumer Satisfaction Measures.

The perceptual parameter estimates enjoy several advantages over satisfaction as measures of quality of care from the perspective of consumers. First, satisfaction and plan choice are simultaneously determined. This simultaneity limits the appropriate use of satisfaction measures in choice

models. Perceptual parameter estimates do not suffer from this problem. This is because they are inferred from choice behavior where attribute importance responses are assumed to be stable characteristics of decision makers. Second, satisfaction is not a valid measure of relative quality. Satisfaction measures reflect enrollees' perceptions of their current plan, not of the set of plan alternatives. By contrast, perceptual parameter estimates allow researchers to make inferences about the relative amount of quality that consumers perceive across a set of plan alternatives. The relative nature of the perceptual parameters facilitates comparison with objective quality measures. Finally, economists may prefer perceptual parameter estimates to satisfaction measures. This is because they are inferred, in part, from actual plan choice behavior and, thus, do not rely solely on subjective survey data.

Limitations.

Perceptual parameter estimation may prove useful in a number of applications of interest to health policy researchers. However, the limitations of the current study raise a number of methodological issues that should be addressed in future research.

Validity of Perceptual Parameters. The validity of the perceptual parameter estimates should be assessed by comparing the findings to those obtained from other methods of measuring perceived quality. Unfortunately, measures

appropriate for this purpose were not included in the Twin Cities survey. In the future, perceived quality measures could be included in consumer surveys that are now routinely collected as part of efforts to measure and monitor the quality of managed care. Unlike consumer satisfaction measures, these survey questions would have to ask respondents to evaluate all of the plans in their choice set. This may be a problem in markets where there are many plan alternatives or when the plan alternatives are not well defined. Alternatively, perceptual parameter estimates could be compared to those obtained from tightly controlled experimental designs that involve hypothetical choices from a clearly defined set of plan alternatives.

Attribute Importance Measures. Recall the study used a measure of attribute importance to capture the heterogeneity of preferences and to identify perceptual parameters representing unobserved attributes in a multiattribute choice model. Because importance measures are not widely used in policy research, the validity and reliability of the importance measures should be more fully understood. This information could be used to develop a measure of importance that more completely captures the relevant dimensions of health plans and meaningful variation across relevant subgroups of respondents.

Three areas deserve particular attention. The first concerns the exogeneity of attribute importance measures. Validity depends on the assumption that choices do not

influence the attribute importance measures. Thus, the fact that in this study attribute importance and choice behavior were observed at the same point in time threatens validity. Potential endogeneity between the attribute importance measures and choices can be avoided if researchers obtain the attribute importance responses prior to observing plan choice. This is difficult in the current Medicare health plan market because opportunities for plan choice are uncoordinated. This would change with the introduction of a competitive bidding scheme and an annual open enrollment period.

The second area concerns consumer definitions of quality. Perceptual parameters estimated in this study represent a composite of several dimensions of quality, including overall quality of care, access to specialists, and not being rushed from the hospital. Research suggests that the interpersonal skills of providers play an important role in consumer assessments of quality. The importance of interpersonal skills may, in fact, be reflected in sample members' assessments of the importance of overall quality. Nonetheless, the validity of the parameter estimates would be strengthened in future applications through the inclusion of an explicit measure of the importance of interpersonal skills of providers.

Finally, care should be taken to assure that the wording of the attribute importance question is consistent with the multiattribute choice model developed in Chapter IV.

Unfortunately, the attribute importance question in the Twin Cities survey is ambiguous. The question asks respondents what attribute would health plans have to have at a 'minimum' to be considered (See Appendix C). This question clearly concerns the importance of plan attributes in the context of plan choice. However, it is not clear whether the question refers to the enrollment choice or to the formation of the decision makers' choice sets prior to the enrollment choice.

Uncertainty Concerning the Choice Set. The validity of the approach also depends on the ability of the model to accurately characterize decision makers' choice sets. Variation in choice sets requires assumptions about the way in which sample members view their choice sets. In this study, the attributes of popular medigap plans were used as proxies, or 'prototypes', for the attributes of medigap plans that were not chosen by sample respondents. The assumption is that sample members viewed their medigap choices in a manner consistent with these prototypes.

It is important to point out that this strong assumption is not required to apply this approach in settings where plan alternatives are well defined. For this reason, the approach used in this study may prove valuable in understanding plan choices of those who choose from a limited number of employer-sponsored plans. In addition, Medicare beneficiaries' choice sets became easier to define and measure with the enactment of medigap standardization legislation in 1990. Finally, this approach may become an

important analytic tool with the enactment and implementation of Medicare competitive bidding proposals. Under this type of a system, beneficiaries could choose among a set of 'qualifying' plan alternatives (Dowd et al., 1996). Presumably, these plans and their characteristics could be easily obtained from the governmental body charged with deciding whether plans meet the qualifying standard.

Summary

This study demonstrated the utility of latent variable approaches for understanding the health plan choices of elderly Medicare beneficiaries. The study concludes with a discussion of the potential applications of choice models that treat unobserved attributes as latent variables. In the future, this approach should help policy makers to better understand the effect on plan choice of otherwise unmeasured attributes, such as quality of care from the perspective of consumers. More importantly, this approach may play a valuable role in developing and evaluating the effects of informational interventions intended to allow elderly decision makers to make meaningful distinctions between technical and interpersonal aspects of care. Nonetheless, a number of methodological issues should be considered in future applications.

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Appendix A: Sampling Weights for Health Plan Choice Model

The likelihood function used in this analysis must be adjusted to account for the over representation of FFS enrollees in the Twin Cities Medicare data set. The Twin Cities data set contains a disproportionate number of respondents in the FFS sector for two reasons. First, a choice-based sampling scheme was used to over-sample FFS enrollees in order to obtain a larger and more reliable sample for estimating FFS Medicare expenditures. Second, HMO enrollees comprise a disproportionate number of non-respondents.

Manski and Lerman (1977) show that, in general, the maximum likelihood estimator (MLE) based on a random (or exogenous) sampling scheme is inconsistent when applied to choice-based samples.¹ Manski and Lerman (1977) propose a modified version of the MLE estimator. This estimator applies a sampling weight, $w(j)$, to each respondent's contribution to the log likelihood.

Model parameters are estimated by maximizing the weighted log likelihood function,

$$(1) \quad L(\theta) = \sum_{i=1}^N \sum_{j=1}^J d_{ij} w(j) \ln P(j|z, \theta)$$

where d_{ij} indicates that person i chose alternative j , z represents the characteristics of the alternatives and decision maker, N is the total number of decision makers and J is the total number of health plans in the choice set.

Following Manski and Lerman (1994), the sampling weight, $w(j)$, is a ratio of the population probability of choosing plan j to the corresponding sample probability. Recall that the analysis is restricted to those less than age 89 in the individual market. Thus, the correct sampling weight for the current analysis can be written

$$(2) \quad w(j) = \frac{Q(j|a = 1, i = 1)}{P(j|a = 1, i = 1)}$$

where $Q(\cdot|\cdot)$ is the conditional population probability of choosing plan j to which the analysis is intended to generalize and $P(\cdot|\cdot)$ is the corresponding sample probability, $a=1$ indicates that the age criterion is met, and $i=1$ indicates that the sample member is in the individual market.

Using Bayes' rule, equation (2) can be expressed as

$$(3) \quad w(j) =$$

$$\frac{Q(a = 1, i = 1|j)Q(j)}{Q(a = 1, i = 1)} \bigg/ \frac{P(a = 1, i = 1|j)P(j)}{P(a = 1, i = 1)}$$

Using the law of total probability to rewrite the joint population and sample probabilities of being in the subgroup of interest, equation (3) can be expressed as

$$(4) w(j) =$$

$$\frac{\sum_{j=1}^J Q(a = 1, i = 1|j)Q(j)}{\sum_{j=1}^J Q(a = 1, i = 1|j)Q(j)} \bigg/ \frac{\sum_{j=1}^J P(a = 1, i = 1|j)P(j)}{\sum_{j=1}^J P(a = 1, i = 1|j)P(j)}.$$

Again, using the law of total probability to rewrite the population and sample probabilities of being in the subgroup of interest conditional on plan choice, equation (4) can be expressed as

$$(5) w(j) =$$

$$\frac{\sum_{j=1}^J [Q(a = 1, i = 1|j, r = 1)Q(r = 1|j) + Q(a = 1, i = 1|j, r = 0)Q(r = 0|j)]Q(j)}{\sum_{j=1}^J [Q(a = 1, i = 1|j, r = 1)Q(r = 1|j) + Q(a = 1, i = 1|j, r = 0)Q(r = 0|j)]Q(j)} \bigg/ \frac{\sum_{j=1}^J [P(a = 1, i = 1|j, r = 1)P(r = 1|j) + P(a = 1, i = 1|j, r = 0)P(r = 0|j)]P(j)}{\sum_{j=1}^J [P(a = 1, i = 1|j, r = 1)P(r = 1|j) + P(a = 1, i = 1|j, r = 0)P(r = 0|j)]P(j)}$$

where $r=1$ indicates that the sample member responded to the survey and $r=0$ indicates that the sample member did not respond to the survey.

The components of equation (5) are either known from outside information or can be estimated from the sample. Consider the denominator first. Both $P(j)$ and

$P(a = 1, i = 1 | j, r = 1)$ are known from the sample. In the analysis of survey non-response, Dowd and others (1994) report values for the sample response probabilities, $P(r = 1 | j)$ and $P(r = 0 | j)$. The probability of being in the subgroup of interest $P(a = 1, i = 1 | j, r = 0)$ conditional on plan choice and not responding to the survey is not directly observable in the sample. However, an estimate of this probability is provided by Dowd and others under the assumption that the conditional probabilities of meeting the age and market membership criteria are independent.

Next, consider the numerator of equation (4). The population enrollment probability, $Q(j)$ is known from outside information provided by HCFA. The population response probabilities, $Q(r = 1 | j)$ and $Q(r = 0 | j)$, can be estimated by the sample response probabilities reported by Dowd and others (1994). This estimate assumes that the population of Twin Cities Medicare beneficiaries contained the sample proportion of people willing to respond to the survey as did the sample. The conditional population probability, $Q(a = 1, i = 1 | j, r = 1)$, is also not known. However, sample information supplies an estimate of this conditional probability that is not biased by the choice-based sampling scheme (Manski, 1994, p.22). Finally, the population probability of being in the subgroup of interest conditional on plan choice and not responding to the survey, $Q(a = 1, i = 1 | j, r = 0)$, is also not known. This quantity can be estimated under the assumption that the population

probability is the same as the corresponding sample probability.

Substitution of outside information and sample estimates of population probabilities simplifies equation (4),

$$(5) \quad w(j) = \frac{Q(j)}{P(j)}.$$

This expression is simply the ratio of the unconditional population choice probability to the unconditional sample probability. This simplification arises because the sample is the only source of information about the value of conditional population probabilities associated with the subgroup of interest. The sampling weights used in this study are listed in Table A.1.

Table A.1: Choice-Based Sampling Weight Components

Health Plan	Sample Probability, $P(j)$	Population Probability, $Q(j)$	Sampling Weight, $w(j)$
Basic Medicare	0.129	0.101	0.783
Medigap without drugs	0.224	0.176	0.786
Medigap with drugs	0.276	0.211	0.789
IPA	0.113	0.176	1.323
Network	0.240	0.328	1.367

Appendix B: Treatment of Missing Fee-For-Service Supplemental Plan Attributes

This appendix describes the treatment of missing FFS supplemental plan attributes. 1,274 respondents in the 1988 Twin Cities Medicare data were in the individual health plan market. 371 of these respondents report having a FFS Medicare supplemental insurance (medigap) plan. The attributes of these medigap plans were documented in a separate survey which collected information about the medigap plan attributes from the companies that sold them.

Unfortunately, this FFS plan data set contains a substantial amount of missing data. There are three types of missing FFS attributes. The first type occurs when the plan attributes are totally missing, meaning the survey contains no information about the attributes of the respondent's plan. The second type occurs when the survey contains partial information about the attributes of the respondent's plan. The third type occurs when the information about a particular attribute is missing for all respondents. The most important situation where this occurs is in the case of FFS premiums. This appendix describes how each of these types of missing data are treated in the analysis.

I. Total Missings

67 of the 371 respondents in the FFS sector have no plan attribute information. The strategy used to treat the total

missing cases involves imputing unknown attributes where possible from similar plans sold by the same company. Four types of cases must be considered to implement this strategy.

Case 1: Company match, one plan (n=9).

This case occurs when the respondent reports a company name that matches another in the data and that company is associated with only one set of plan attributes. This case occurs several times in association with medigap plans sold by United American and Mutual of Omaha. When this case arises, the missing attributes are simply imputed from the single set of known attributes associated with that company.

Case 2: Blue Cross-Blue Shield plan code match (n=10).

This case occurs when the respondent reports having a Blue Cross-Blue Shield plan and the plan code recorded by the interviewer matches other plan codes where attributes are known. When this case arises, the missing attributes are imputed from the plan with the matching BC-BS code.

Case 3: Company match, many plans (n=42).

This case occurs when the respondent reports a company name that matches another in the data and that company is associated with several different sets of attributes. This occurs in the case of the plans sold by the American Association of Retired Persons and by Blue Cross-Blue Shield.

When this case arises, the missing attributes are imputed from the modal plan sold by each company.

Case 4: No company match (n=17).

This case occurs when there does not appear to be an appropriate company match from which to impute attributes. In this case, attributes of a prototype FFS medigap policy are used as a proxy for the missing attributes. This prototype is similar to that assigned to respondents who did not choose a medigap plan.

II. Partial Missing Attributes.

The FFS data set contains at least some plan attribute information for 303 of 371 respondents who report having a FFS supplement. Imputing the partially missing attributes is challenging because it is not known whether attributes are missing simply because the benefit is not covered by the plan or because the plan covers the benefit and the amount of the benefit is not known. The strategy used to impute partially missing attributes is similar to that used to impute totally missing attributes. However, the imputation process involves several additional steps aimed at assuring that error is in the direction of making the plan less rather than more comprehensive. This conservative strategy is based on the observation in the retiree health insurance literature (which is consistent with the pattern in the Twin Cities data) that

comprehensive plans are relatively rare (Rice, 1987; McCall et al., 1986; Cafferata, 1984).

Step 1: Identify whether the pattern of missing attributes suggests that the respondent had some other type of plan that was reported as supplemental coverage. Sixteen respondents have missing attributes consistent with enrollment in a hospital indemnity plan and four respondents appear to have drug riders as their only type of supplemental coverage. Although hospital indemnity plans and drug riders are not, technically speaking, Medicare supplemental insurance, this analysis treats them as such. The justification is that (1) these plans are bundled with some of the same coverage provided by medigap policies and (2) respondents perceive these plans to be a form of supplemental insurance.

If these alternative plans are to be treated like medigap plans, then the services that they cover must be converted into equivalent medigap coverage. For hospital indemnity plan, the daily rate times the average hospital length of stay for a person over age 65 (8 days) is assigned as the hospital deductible. This assumes that the decision maker would apply the indemnity payment toward the Medicare deductible and that the decision maker considers an average length of stay and the amount of the Part A deductible in choosing the size of the indemnity to purchase. Drug riders are more straightforward: drugs and whatever services are

also listed in the bundle are assigned as the only non-zero attributes.

Step 2: Identify whether the non-missing attributes indicate a 'front-end' or 'back-end' plan. If the plan appears to be a front-end plan, then missing back-end attributes are assumed to indicate that the benefit is not covered by the plan. If the plan appears to cover back-end expenses, then missing front-end attributes are assumed to indicate that the benefit is not covered by the plan.

Step 3: Identify plans sold by the same company where non-missing attributes match. Impute missing attributes from within the same company without breaking the 'front-end, back-end' rule discussed in Step 2.

Step 4: When no matching company can be found, identify plans with similar benefits sold by a different company. Impute missing attributes from within the same company without breaking the 'front-end, back-end' rule discussed in Step 2.

Step 5: When no acceptable match can be found, it is assumed that the missing benefit is not covered by the plan.

III(a). Missing Premiums.

The Twin Cities data contains no premium information. Premiums for FFS plans are estimated from a 1990 survey of medigap premiums conducted by the State of Minnesota (Minnesota Department of Commerce, 1990). The plans reported

by Twin Cities survey respondents are matched with the average premium for a similar plan as reported by the Department of Commerce. There are two problems with this strategy. First, the premiums reported by the Department of Commerce are expected to be higher than the average premium paid by the survey respondents because of inflation and standardization legislation. Standardization legislation enacted in 1990 required that consumers be able to choose from a fixed menu of benefits. This law means that companies could no longer bundle benefits together to reduce adverse selection in order to reduce costs (i.e. drug benefits are commonly sold with high Part B deductibles). There is no readily available source of information about medigap premiums to use in correcting the potential bias. However, the upward bias does not change the ordering of plan premiums, because medigap plans are the most expensive alternative even without upward bias. Also, in comparing estimated premiums to medigap premiums reported by Consumer Reports ("Beyond Medicare", 1989), the estimated premiums appear to account for the relative prices of alternative bundles of services within the FFS sector fairly well, despite the possible bias.

Second, the Department of Commerce does not report average premiums for outpatient prescription drugs or care in a skilled nursing facility (SNF) beyond 150 days. The incremental premium value of these widely held benefits must be estimated from additional sources of information. The

incremental premium associated with outpatient prescription drug benefits is estimated to be \$375 per year. This estimate represents a 'good guess' arising from a number of sources: (1) the range of premiums (\$305-\$565 per year) charged by particular insurers for riders that cover at least 75 percent of the cost of drugs as reported to the Department of Commerce, (2) an estimate of the incremental cost (\$195-\$531) of drugs across plans with otherwise similar benefits as reported in a 1989 review of medigap plans in Consumer Reports ("Beyond Medicare", 1989) and (3) the incremental cost (\$225-\$360 per year) of a drug rider charged by Blue Cross-Blue Shield for the Senior Gold PPO. The incremental premium associated with care in a SNF beyond 150 days is estimated to be \$55 year. This estimate represents the difference in premium between a plan with extra SNF (as reported in the Department of Commerce Report) and a plans with otherwise similar benefits as reported in Consumer Reports ("Beyond Medicare", 1989).

Premiums for drug rider plans are also assumed to be \$375 per year plus the incremental premiums for additional benefits, usually care in a SNF beyond 150 days (Minnesota Department of Commerce, 1990). Consistent with the literature on retiree health insurance, drug benefits are most often bundled with extra SNF in the Twin Cities data set.

III(b). Other Missing Attributes.

The overwhelming majority of values for coverage of hospital stays longer than 365 days and limits on out-of-pocket expenditures are missing. Consistent with the literature on the elderly's health insurance (Rice, 1987; McCall et al., 1986; Cafferata, 1984), FFS supplements are assumed not to cover these benefits. In addition, all FFS plans are assumed to cover the SNF copayment and the 20 percent Part B coinsurance for Medicare approved charges.

Appendix C: Survey Questionnaire

Sequence No. _____

Before we begin, we want to double-check the information you gave us over the telephone.

1. Do you receive SSI (Supplemental Security Income) or disability benefits from Social Security?

YES..... 1--->PROBE. LOOK AT SSI CARD.
IF NECESSARY, STOP INTERVIEW.
TELL RESPONDENT THAT THE STUDY
IS LIMITED TO PEOPLE NOT
ELIGIBLE FOR DISABILITY
BENEFITS. THANK & TERM.
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

2. Are you eligible for Medical Assistance (Medicaid)?

YES..... 1--->PROBE. LOOK AT MEDICAID CARD.
STOP INTERVIEW. TELL
RESPONDENT THAT THE STUDY IS
LIMITED TO PEOPLE NOT ELIGIBLE
FOR MEDICAL ASSISTANCE. THANK
THE RESPONDENT FOR HIS/HER
TIME.
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

3. Are you presently employed or is your spouse presently employed?

YES..... 1--->ASK Q.4
NO..... 2
DON'T KNOW..... 8
REFUSED..... 9
1--->SKIP TO Q.5

4. Do you have health insurance where you work or where your spouse works?

YES..... 1--->And does this insurance pay before
Medicare pays?
YES..1--->THANK & TERM
NO...2--->Is this insurance a
supplemental policy?
YES..1--->CONTINUE
NO...2--->THANK & TERM.
NO..... 2
DON'T KNOW..... 8
REFUSED..... 9
1--->CONTINUE

5. Now I just need to confirm your age. Would you please tell me your age?

YEARS:
NOT APPLICABLE.... 97 1--->SKIP TO Q.7
DON'T KNOW..... 98 --->ASK Q.6
REFUSED..... 99 --->ASK Q.6

6. Would you please tell me which of the following age groups you are in? READ LIST

Under 65..... 1
65 to 74..... 2
75 to 84..... 3
Over 85..... 4
NOT APPLICABLE.... 7
DON'T KNOW..... 8
REFUSED..... 9

Sequence No.

Now, I'm going to ask you some questions about your health insurance coverage.

7. First, may I see your Medicare card and any other health plan card(s) to make sure that I have the current health plan information?

YES..... 1-----CIRCLE ANSWERS AT 0.8 AND 0.9
AND FILL IN CARD INFORMATION SHEET
NO..... 2 1
NOT APPLICABLE..... 7 1
DON'T SHOW..... 8 1--->ASK 0.8 AND 0.9 AS QUESTIONS AND
REFUSED..... 9 1 SKIP TO 0.13

8. CHECK MEDICARE CARD AND CIRCLE YES OR NO.

IF NO CARD, ASS:

Are you currently covered by...

- a. Medicare Part A (the part that covers hospitalization)?

YES..... 1--->SKIP TO 0.10
NO..... 2 1
DON'T SHOW..... 3 1--->ASK 0.8
REFUSED..... 4 1

- b. Are you eligible for railroad retirement benefits?

YES..... 1
NO..... 2
DON'T SHOW..... 3
REFUSED..... 4

- c. Medicare Part B (the part that covers doctors' bills)?

YES..... 1
NO..... 2
DON'T SHOW..... 3---> ASS: Is the premium deducted
from your social security
REFUSED..... 4

9. NAME OF PRIMARY PLAN FROM CARD

IF NO CARD, ASS: What is the name of your current health plan?

PHP (Physician's Health Plan)-Select Plan..... 1
PHP (Physician's Health Plan)-Choice Plan..... 2
PHP (Physician's Health Plan)-Unspecified..... 3
Med Center Health Plan..... 4
HMO Minnesota..... 5
Group Health..... 6
Regular Medicare..... 8
NOT APPLICABLE..... 97
DON'T SHOW..... 98
REFUSED..... 99

IF NO CARD, SKIP TO 0.13 IF CARD(S), CONTINUE.

SOLD UP CARD FOR PLAN CIRCLED AT 0.9 ASS:

10. Is this your current health plan?

YES..... 1--->SKIP TO 0.13
NO..... 2--->ASK 0.11
NOT APPLICABLE..... 7 1
DON'T SHOW..... 8 1--->SKIP TO 0.13
REFUSED..... 9 1

Sequence No.

11. What is the name of your current health plan?

PHP (Physician's Health Plan)-Select Plan..... 1
PHP (Physician's Health Plan)-Choice Plan..... 2
PHP (Physician's Health Plan)-Unspecified..... 3
Med Center Health Plan..... 4
HMO Minnesota..... 5
Group Health..... 6
Regular Medicare..... 8
OTHER (SPECIFY)..... 9
NOT APPLICABLE..... 97
DON'T SHOW..... 98
REFUSED..... 99

12. How long ago did you change from G.S. PLAN to G.I. PLAN?

MONTH YEAR

NOT APPLICABLE..... 9997
DON'T SHOW..... 9998
REFUSED..... 9999

13. Do you have any insurance policies that supplement your G.I. PLAN? That is, a policy that pays for whatever G.I. PLAN was't, or that provides any additional coverage?

YES..... 1--->IF CARD, ASS 0.14
IF NO CARD, ASS 0.15
NO..... 2 1
NOT APPLICABLE..... 7 1
DON'T SHOW..... 8 1--->SKIP TO 0.17
REFUSED..... 9 1

IF CARD, SOLD UP AND ASS:

14. Is this the name of the plan that supplements your G.I. PLAN?

YES..... 1--->RECORD AT 0.15
NO..... 2--->RECORD PLAN ON CARD AND ASS 0.14

15. What is the name of the plan that supplements your G.I. PLAN?

Aid Association for Lutherans..... 1
Eliu Greese/Eliu Shield (Senior Old
or Medicare Supplement Plan)..... 2
Central States Health and Life..... 3
Group Health (Senior Plus)..... 4
HMO Minnesota..... 5
Med Center (Senior Choice)..... 6
Mid-American Life..... 7
Mutual Service Life..... 8
Savannah Travelers Life..... 9
Physicians Health Plan..... 10
Prudential (GAMP)..... 11
Principal Mutual Life..... 12
Shaw..... 13
State Farm..... 14
OTHER (SPECIFY)..... 15
NOT APPLICABLE..... 97
DON'T SHOW..... 98
REFUSED..... 99

Sequence No. _____

16. When did you enroll in INSERT HEALTH PLAN FROM 9.157

MONTH YEAR
NOT APPLICABLE..... 9997
DON'T KNOW..... 9999
REFUSED..... 9999

17. Does people purchase health insurance coverage through a group policy. Do you obtain any of your health insurance through a group policy?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8 [--->SKIP TO 0.19
REFUSED..... 9

18. Who is the sponsor of the group policy?

RESPONDENT'S FORMER EMPLOYER..... 1
SPOUSE'S FORMER EMPLOYER..... 2
FRATERNAL OR SENIOR ORGANIZATIONS..... 3
OTHER (SPECIFY)..... 4
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

19. Does anyone, other than you or your family members, pay any part of the premium for ANY of your current health insurance policies?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8 [--->SKIP TO 0.21
REFUSED..... 9

20. Who pays part or all of your health insurance premiums?

RESPONDENT'S FORMER EMPLOYER..... 1
SPOUSE'S FORMER EMPLOYER..... 2
FRATERNAL OR SENIOR ORGANIZATIONS..... 3
OTHER (SPECIFY)..... 4
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

Sequence No. _____

21. Now, I'd like you to think about the following features of your current health plan(s). Are you Very Satisfied (VS), Satisfied (S), Dissatisfied (DS), or Very Dissatisfied (VD) with these features? (GIVE RESPONSE CARD TO RESPONDENT) NOTE: NA (NOT APPLICABLE)-NO EXPERIENCE UNDER PLAN AT THIS TIME.

The first feature is.... VE VS S DS VD NA DS REF

a. The amount you pay each month to belong to your health plan..... 1 2 3 4 7 8 9
b. The extent you have to pay the doctor or hospital when your health insurance doesn't pay (includes deductible and coinsurance)..... 1 2 3 4 7 8 9
c. The option to see the physician of your choice..... 1 2 3 4 7 8 9
d. The option to go to the hospital of your choice..... 1 2 3 4 7 8 9
e. Not "rushing the patient out of the hospital"..... 1 2 3 4 7 8 9
f. The wait for an appointment to see a doctor..... 1 2 3 4 7 8 9
g. The wait in the doctor's office..... 1 2 3 4 7 8 9
h. Physician's willingness to refer you to a specialist if necessary..... 1 2 3 4 7 8 9
i. The overall quality of care..... 1 2 3 4 7 8 9
j. Amount of paperwork overall..... 1 2 3 4 7 8 9
k. Convenience of the location of clinic or doctors' office..... 1 2 3 4 7 8 9
l. Convenience of the hours for clinics or doctors' office..... 1 2 3 4 7 8 9
m. Are there other service or coverage features that I haven't mentioned that you would like to mention? (SPECIFY)..... 1 2 3 4 7 8 9
n. Overall, how would you rate your current health plan, that is, SUGGESTION: Would you say you are Very Satisfied, Satisfied, Dissatisfied or Very Dissatisfied?..... 1 2 3 4 7 8 9

22. Now, I'm going to read a list of health plans that are available to Medicare enrollees in the Twin Cities. I'd like you to tell me if you've HEARD, SEEN, or any of the following plans. (GIVE CARD: MCAR LIST)

The first one is PMP (Physician's Health Plan)....
IF HEARD ABOUT, ASK FOR "CHOICE" PLAN AND "SPECIFY" PLAN. IF NOT, SKIP TO "d".

HEARD NOT
ASKED OR REF

a. PMP (Physician's Health Plan)-No Spec. Plan..... 1 2 3 9
b. PMP (Physician's Health Plan)-Choice Plan..... 1 2 3 9
c. PMP (Physician's Health Plan)-Select Plan..... 1 2 3 9
d. Med Center Health Plan..... 1 2 3 9
e. HMO Minnesota..... 1 2 3 9
f. Group Health..... 1 2 3 9
g. There..... 1 2 3 9
h. Policies that supplement your basic Medicare coverage (SPECIFY)..... 1 2 3 9

IF NOT HEARD OF ANY ABOVE, SKIP TO 0.26

Sequence No. _____

23. Thinking of the plans you have heard about, have you ever looked into what these plans cost and what services they offer?

NO..... 2---)SKIP TO 0.2R

SOMEONE ELSE
DOES FOR ME... 3---) 23a. Do you make the decision about which plan to belong to or does (PERSON)?

I DECIDE/JOINT... 1---)GO TO 0.23b
PERSON DECIDES... 2---) I have a few questions for PERSON.
May I have a name and phone number?

REFUSED..... 00

SKIP TO 0.24

YES..... 1---) 23b. When was the last time you looked into the costs and services of a health plan?

MONTH YEAR

DON'T KNOW..... 0000

REFUSED..... 0000

24. At that time, was there a particular doctor's office, clinic, health center or other place you would usually go to if you got sick or needed advice about your health?

YES..... 1---)SKIP 0.25

NO..... 2 : 1

NOT APPLICABLE..... 7 : 1

DON'T KNOW..... 8 : 1---)SKIP TO 0.26

REFUSED..... 9 : 1

25. (ASK ONLY FOR PLANS WITH RESPONSE = "HEARD ABOUT" IN Q.22
--LEAVE OTHERS BLANK)

At that time in MONTH/YEAR FROM Q.23, would (INSERT EACH FROM Q.22) have allowed you to continue using your (INSERT) plan?

NOT
YES NO APPLY DK REF

a... PHP (Physicians Health Plan)-No Specific Plan..... 1 2 7 8 9
b... PHP (Physicians Health Plan)-Choice Plan... 1 2 7 8 9
c... PHP (Physicians Health Plan)-Select Plan... 1 2 7 8 9
d... Med Center Health Plan..... 1 2 7 8 9
e... UMO Missions..... 1 2 7 8 9
f... Group Health..... 1 2 7 8 9
g... Others..... 1 2 7 8 9
h... Policies that supplement your health
Medicare coverage..... 1 2 7 8 9

Sequence No. _____

9. If you had to change your health plan for any reason, which of the following features would a health plan have to have at a minimum for you to consider it? For each feature that I read, please tell me if you would "have to have" it, "like to have" it, or "doesn't matter" to consider a plan. (OIVE CARD. READ LIST.)

The first feature is...

HAVE LIEK DOESN'T
TO TO MATTER DK REF

a... You pay the lowest possible amount each month to belong to the plan... 1 2 7 8 9
b... You pay the lowest possible amount to the doctor or hospital when your health insurance doesn't pay the full bill..... 1 2 7 8 9
c... Coverage of prescription drugs 1 2 7 8 9
d... Coverage of eyeglasses 1 2 7 8 9
e... Coverage of preventive care such as regular checkups..... 1 2 7 8 9
f... The option to see any physician of your choice 1 2 7 8 9
g... The option to go to any hospital of your choice 1 2 7 8 9
h... Not being "pushed out of the hospital" 1 2 7 8 9
i... Shortest possible wait for an appointment to see a doctor..... 1 2 7 8 9
j... Shortest possible wait in doctor's office..... 1 2 7 8 9
k... Physicians who refer their patients to specialists when necessary..... 1 2 7 8 9
l... Highest possible quality of care overall..... 1 2 7 8 9
m... Minimum possible paperwork overall..... 1 2 7 8 9
n... Convenient location of clinic or doctors' office 1 2 7 8 9
o... Convenient hours for clinics or doctors' office 1 2 7 8 9
p... Are there other service or coverage features that I haven't mentioned that you would like to comment on?
(SPECIFY)..... 1 2 7 8 9

27. What is your MOST IMPORTANT source of information about the Medicare health plan options available to you now? (OIVE RESPONDENT RESPONSE CARD. TRY FOR ONLY ONE, CODE MULTIPLE SOURCES "COMBINATIONS".)

Advertisements in newspapers..... 1
Advertisements on television..... 2
Advertisements on the radio..... 3
Advertisements through the mail..... 4
Talking to friends and relatives..... 5
Talking to a physician or other health professional..... 6
Your own experience in health plans..... 7
NONE..... 8
OTHER (SPECIFY)..... 9
COMBINATIONS (TIE) OF THE ABOVE..... 4
DON'T KNOW..... 9R
REFUSED..... 9R

Sequence No.

28. I am going to read a list of services that some people receive. Please tell me if you have received any of these services **DURING THE PAST 3 MONTHS SINCE 1988**.
Have you received... (READ ONE AT A TIME, CIRCLE UNDER 0.28)

29. FOR EVERY "YES" IN 0.28 ARE: You mentioned receiving _____
Was this service provided by a
relative or friend? (CIRCLE UNDER 0.29)
(IF RELATIVE/FRIEND AND OTHER PARTIES,
CIRCLE "1" FOR "BOTH" AND ASK 0.30
FOR OTHER PARTIES ONLY.
30. FOR EVERY "NO" IN 0.28 ARE: Approximately how many times
have you used this service in
the past 3 months?

-----0.28----- 0.28-----
NO DK REF YES YES DK REF NO/1
NOT

- a. Housework services such
as housekeeping, laundry,
shopping, and errands?..... 2 8 8 3 2 8 9 (--)_____visits
- b. Some health aide services
such as help with bathing,
feeding, or walking?..... 2 8 8 1 2 8 8 (--)_____visits
- c. Some nursing care?..... 2 8 8 1 2 8 8 (--)_____visits
- d. Adult day care?..... 2 8 8 1 2 8 8 (--)_____days
- e. Meals on wheels or
congregate dining?..... 2 8 8 1 IF 0.28 YES (--)_____meals
- f. Transportation services?..... 2 8 8 1 2 8 8 (--)_____one-way trips

31. Now I'm going to read you a list of health conditions.
Please tell me if you have any of them at the present time.

So you have... (READ ONE AT A TIME, FOR ANY RESP. "USED TO
HAVE" ARE...)

Is that still a problem for you?

NOT
YES NO APPLY DK REF

- a. High blood pressure..... 1 2 7 8 9
b. Diabetes..... 1 2 7 8 9
c. Asthma, emphysema, or chronic
bronchitis..... 1 2 7 8 9
d. Anemia..... 1 2 7 8 9
e. Heart trouble or angina..... 1 2 7 8 9
f. Circulation problems or
hardening of the arteries..... 1 2 7 8 9
g. Paralysis or effects of a stroke..... 1 2 7 8 9
h. Nerve or muscle problems like
Parkinson's disease or multiple sclerosis..... 1 2 7 8 9
i. Arthritis or rheumatism..... 1 2 7 8 9
j. A tumor or a cancer other than
a skin cancer..... 1 2 7 8 9
k. Chronic skin problems..... 1 2 7 8 9
l. Digestive problems such as ulcers,
stomach or bladder trouble, or colitis..... 1 2 7 8 9
m. Liver problems such as cirrhosis..... 1 2 7 8 9
n. Kidney or bladder problems (MEN
including prostate)..... 1 2 7 8 9
o. Speech problems..... 1 2 7 8 9
p. Hearing problems..... 1 2 7 8 9
q. Mental health problems..... 1 2 7 8 9

Sequence No.

32. Do you smoke cigarettes, cigars, or a pipe?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

33. How long have you been a smoker?

YEARS
"ALL MY LIFE"..... 98----> EDITOR: FILL IN YEARS
NOT APPLICABLE..... 97 FROM 0.5 OR 0.8
DON'T KNOW..... 96
REFUSED..... 95

34. How much do you usually smoke in a day?

a. cigarettes
b. cigars
c. pipe
NOT APPLICABLE..... 97
DON'T KNOW..... 96
REFUSED..... 95

35. (I know you said you don't currently smoke, but) Have you
ever smoked cigarettes, cigars, or a pipe?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

36. How long were you a smoker?

YEARS
NOT APPLICABLE..... 97
DON'T KNOW..... 96
REFUSED..... 95

37. When did you quit smoking?

YEARS AGO
NOT APPLICABLE..... 97
DON'T KNOW..... 96
REFUSED..... 95

38. How much did you usually smoke in a day?

a. cigarettes
b. cigars
c. pipe
NOT APPLICABLE..... 97
DON'T KNOW..... 96
REFUSED..... 95

Sequence No.

The questions I'm going to ask now have to do with how you manage with several routine daily activities. For the purposes of this research study, we need to ask these questions for all respondents, regardless of how well they manage. When answering these next few questions, please think about what you are physically ABLE to do, not necessarily what you ACTUALLY do.

39. First, can you get to places out of walking distance without help, that is, can you travel alone on buses or taxis, or drive your own car?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

40. Assuming you have transportation, can you go shopping for groceries or clothes without help?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

41. Are you physically able to prepare your own meals yourself?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

42. Can you do your own daily housework without help?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

43. If you had medicine to take, could you take it without help, is the right dose at the right time?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

44. Can you handle your own money, such as writing checks and paying bills without help?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

Sequence No.

45. Can you do the following without any help....(READ ONE AT A TIME)

a. dress and undress...

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

b. take care of your own appearance such as combing your own hair or shaving...

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

c. feed yourself with no help...

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

d. get in and out of bed...

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

e. take a bath or shower...

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

f. Do you ever have trouble getting to the bathroom on time?

YES..... 1
NO..... 2
NOT APPLICABLE..... 7
DON'T KNOW..... 8
REFUSED..... 9

46. Which of the following best describes your control of your urination and bowel movements: you never have accidents, occasionally you have accidents, you have frequent accidents or you are incontinent, or you use a catheter or colostomy bag? Please read to the author of the response that best describes you. (USE RESPONSE CARD)

Never have accidents..... 4
Occasionally you have accidents..... 3
Too have frequent accidents or are incontinent..... 2
You use a catheter or colostomy bag..... 1
Not applicable..... 7
Don't know..... 8
Refused answer..... 9

Sequence No.

47. I am going to read a list of activities you might do. If you do not do these activities, please tell me how much trouble it would be to do them. For each activity please tell me whether it would be no trouble at all, some trouble, a lot of trouble or that you can't do it at all. (CITE RESPONDENT THE RESPONSE CARD)

The first one is... (READ ONE AT A TIME)

	NO	SOME	A LOT	CAN'T	NOT	TRBL	DO	APPL	DE	REF
a... Walking one block.....	1	2	3	4	5	6	7	8	9	
GO TO D										
b... Walking several blocks....	1	2	3	4	5	6	7	8	9	
GO TO D										
c... Walking more than a mile..	1	2	3	4	5	6	7	8	9	
d... Going up one flight of stairs.....	1	2	3	4	5	6	7	8	9	
GO TO F										
e... Going up several flights of stairs.....	1	2	3	4	5	6	7	8	9	
f... Lifting, kneeling or stooping.....	1	2	3	4	5	6	7	8	9	
g... Doing activities such as mowing a lawn or pushing a vacuum cleaner.....	1	2	3	4	5	6	7	8	9	
h... Doing activities such as lifting heavy objects....	1	2	3	4	5	6	7	8	9	
i... Lifting or carrying groceries.....	1	2	3	4	5	6	7	8	9	
j... Doing activities such as running to the bus.....	1	2	3	4	5	6	7	8	9	

48. I am going to read you a list of statements about how you might be feeling at any particular time. For each statement please tell me if you were feeling that way most of the time, some of the time, very little of the time or none of the time during the past month alone. (CITE RESPONDENT THE RESPONSE CARD)

The first is... (READ EACH ANV RECORD BLOW)

	NOT	SOME	LITTLE	NONE	NOT	TIME	TIME	TIME	TIME	APPL	DE	REF
a... Generally enjoying things?	1	2	3	4	5	6	7	8	9			
b... Tense or keyed up? (being nervous or anxious).....	1	2	3	4	5	6	7	8	9			
c... Feeling cheerful.....	1	2	3	4	5	6	7	8	9			
d... Not able to "get going"....	1	2	3	4	5	6	7	8	9			
e... Feeling depressed.....	1	2	3	4	5	6	7	8	9			
f... Feeling hopeful about the future.....	1	2	3	4	5	6	7	8	9			
g... Feeling sad.....	1	2	3	4	5	6	7	8	9			
h... Embarrassed by trembling (or shaking).....	1	2	3	4	5	6	7	8	9			
i... Feeling that something bad was going to happen to you.....	1	2	3	4	5	6	7	8	9			

Sequence No.

49. Now, a few questions about you and your family. How long have you lived in the Twin Cities metropolitan area?

MONTHS or YEARS
 "ALL MY LIFE"..... 98--> EDITOR: FILL IN YEARS
 NOT APPLICABLE..... 97
 DON'T KNOW..... 98
 REFUSED..... 99

50. In the past year did you live in the Twin Cities metropolitan area year round?

YES..... 1-->SKIP TO Q.52
 NO..... 2-->ASK Q.51
 NOT APPLICABLE..... 97
 DON'T KNOW..... 98
 REFUSED..... 99

51. Which months did you spend elsewhere?

MONTH to MONTH
 NOT APPLICABLE..... 97
 DON'T KNOW..... 98
 REFUSED..... 99

52. Are you? (READ OPTIONS)

currently married..... 1
 widowed..... 2
 divorced or separated..... 3
 single or never married..... 4
 NOT APPLICABLE..... 7
 DON'T KNOW..... 98
 REFUSED..... 99

53. Do you live alone?

YES..... 1
 NO..... 2
 NOT APPLICABLE..... 7
 DON'T KNOW..... 98
 REFUSED..... 99

54. How many living children do you have?

children (IF "NONE", SKIP TO Q.55)
 NOT APPLICABLE..... 97
 DON'T KNOW..... 98
 REFUSED..... 99

55. How many of your children live within one hour's driving time of where you live, including those who may live with you?

children
 NOT APPLICABLE..... 97
 DON'T KNOW..... 98
 REFUSED..... 99

Sequence No. _____

56. Which category best describes the highest grade in school that you have completed? GIVE RESPONSE CARD.

... Grades 1-7 (some grade school)..... 1
 ... Grade 8 (completed grade school)..... 2
 ... Grades 9-11 (some high school)..... 3
 ... Grade 12 (high school diploma or G.E.D.)
 (IF G.E.D. ASS IF THEY HAVE DIPLOMA)..... 4
 ... Technical or vocational school
 without H.S. diploma..... 5
 ... Technical or vocational school
 with H.S. diploma..... 6
 ... Some college (grades 13 to 15)..... 7
 ... College Degree (grade 16)..... 8
 ... Graduate or professional education in
 excess of college degree..... 9
 NOT APPLICABLE..... 97
 DON'T KNOW..... 98
 REFUSED..... 99

57. Which of the following groups do you consider to be your ethnic group? (READ LIST)

White..... 1
 Black..... 2
 American Indian or
 Alaskan native... 3
 Asian American or
 Pacific Islander... 4
 Hispanic..... 5
 OTHER (SPECIFY)..... 6
 NOT APPLICABLE..... 7
 DON'T KNOW..... 8
 REFUSED..... 9

58. What is your height?

feet inches
 DON'T KNOW..... 998
 REFUSED..... 999

59. What is your weight?

pounds
 DON'T KNOW..... 998
 REFUSED..... 999

60. In general, would you say your health is: (READ OPTIONS)

Excellent..... 1
 Good..... 2
 Fair..... 3
 Or, poor..... 4
 NOT APPLICABLE... 7
 DON'T KNOW..... 8
 REFUSED..... 9

61. Comparing your general health to other people your own age, would you say your health is Much Better, Better, About the Same, Worse or Much Worse?

MUCH BETTER.... 1
 BETTER..... 2
 THE SAME..... 3
 WORSE..... 4
 MUCH WORSE.... 5
 NOT APPLICABLE... 7
 DON'T KNOW..... 8
 REFUSED..... 9

happen in you.....

Sequence No. _____

62. During each of the past 12 months since INSERT DATE, were you (READ ONE AT A TIME)

Employed full-time... 1
 Employed part-time... 2
 Not employed outside
 the home..... 3
 OTHER..... 4
 NOT APPLICABLE... 7
 DON'T KNOW..... 8
 REFUSED..... 9

63. What was your occupation during each of your life? (PHONE FOR SPECIFIC OCCUPATION AND JOB TITLE)

OFFICE USE ONLY Job code

64. During the past year since INSERT DATE, what was your (and your spouse's) approximate total income before taxes? Please include all sources such as wages, salaries, social security, pensions, investments and so forth.

NOT APPLICABLE... 998989-1
 DON'T KNOW..... 999989-1
 REFUSED..... 999989-1-999989-1

65. If you cannot tell us the exact amount, can you give us an estimate? Is your total income... (USE RESPONSE CARD)

less than \$10,000 per year... 1
 \$10,001- \$20,000..... 2
 \$20,001- \$30,000..... 3
 \$30,001- \$40,000..... 4
 \$40,001- \$50,000..... 5
 more than \$50,000..... 6
 NOT APPLICABLE... 7
 DON'T KNOW..... 8
 REFUSED..... 9

66. GENDER (BY OBSERVATION):

FEMALE..... 1
 MALE..... 2

Sequence No. _____

We would like to contact you in the future to find out if you are still enrolled in the same health plan. Could you please tell us the name, address, and telephone number of two people who will know where to locate you - just in case you move between now and the next time we would like to speak with you?

NAME _____
 ADDRESS _____
 CITY _____ STATE _____ ZIP _____
 PHONE _____ RELATIONSHIP TO RESP _____

NAME _____
 ADDRESS _____
 CITY _____ STATE _____ ZIP _____
 PHONE _____ RELATIONSHIP TO RESP _____

(INTERVIEWER: DO NOT ASK)

57. DOES RESPONDENT AGREE TO A FOLLOW-UP?

YES... 1
 NO.... 2

Thank you for participating in this survey. I want you to know that the information you provided will help the government improve health care services for persons like yourself.

Once again, thank you for your time.

GIVE RESPONDENT RIS/NER GRATUIT

(INTERVIEWER: DON'T ASK)

58. Who responded to the survey?

Medicare client..... 1
 Medicare client with help of family member/friend... 2
 Medicare client in combination with family member/
 friend (0.22 to 0.27 sequence)..... 3
 Family member/friend (proxy respondent)..... 4

Proxy's Name Relationship to Enrollee

Name(s) of other(s) present Relationship to Enrollee

59. The site of interview is:

Enrollee's home..... 1
 Another person's home..... 2
 Hospital..... 3
 Nursing home..... 4
 OTHER (SPECIFY)..... 5

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C.2

